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A Machine Learning-Enhanced Telehealth System for Remote Postnatal Monitoring: Design and Evaluation at Chinhoyi Provincial Hospital, Zimbabwe

BY

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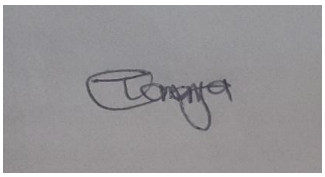
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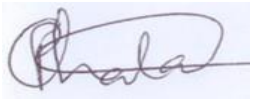
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DEDICATION

This work is especially dedicated to my mother, whose endless effort, encouragement and perseverance have been constant source of strength throughout my academic journey. Through every difficult moment, your belief in me never wavered, and it is that belief that carried me to the completion of this work. Above all, l dedicate this project to the Almighty God, for the unwavering support and guidance during moments when l hit rock bottom, for granting me strength, clarity of mind and the ability to complete this study.

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Abstract

Maternal and neonatal mortality remain critical public health challenges in Zimbabwe, particularly in remote communities where access to consistent postnatal healthcare is constrained by geographical distance, infrastructure limitations and shortages of skilled health workers. This study addresses these challenges through the design, development and evaluation of a machine learning-enhanced telehealth system for remote postnatal monitoring, contextualized at CPH, Zimbabwe. The system employs Artificial Neural Networks trained on clinically grounded synthetic datasets to classify maternal and neonatal health risk into three categories: low, medium and high. The research pipeline encompassed dataset preprocessing, including MinMaxScaler normalization and label encoding, ANN model training with EarlyStopping and ModelCheckpoint callbacks and rigorous evaluation using accuracy metrics, confusion matrices and classification reports. The maternal risk prediction model achieved a test accuracy of 99%, with perfect precision and recall on high risk cases, while the neonatal model demonstrated comparable performance. The trained models were deployed within a Flask-based web application proving real-time prediction, patient health record management and an integrated clinical-patient email communication feature. The findings confirm that machine learning-enhanced telehealth systems can provide accurate, reliable and deployable postnatal risk classification support, offering a practical pathway for extending maternal and neonatal healthcare to geographically remote and resource-constrained populations.

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List of Acronyms and Abbreviations

DL	Deep Learning
ML	Machine Learning
ANN	Artificial Neural Network
CPH	Chinhoyi Provincial Hospital

Chapter 1

1.1 INTRODUCTION

This study addresses the design, development, and evaluation of a telehealth system aimed at improving postnatal maternal and neonatal care at Chinhoyi Provincial Hospital. In this context, 'enhancing' refers to strengthening the quality, accessibility, and effectiveness of healthcare services through the use of digital technologies. By leveraging telehealth solutions, the study seeks to support remote monitoring, improve communication between healthcare providers and postnatal mothers, and enable early diagnosis of potential complications. Ultimately, the goal is to reduce preventable health risks and improve outcomes for postnatal mothers and newborns.

This chapter lays the foundation of the study by presenting the background to the research, the problem statement, research objectives, and research questions. It also provides the justification for the study, defines its scope, and outlines the overall structure of the research. Together, these elements establish the context for the chapters that follow.

1.2 Background to the study

Global Context

Maternal and neonatal health remain critical major public health priorities, particularly in low- and middle-income countries (LMICs), where most preventable deaths occur. Globally, an estimated 287 000 women died due to pregnancy and childbirth-related complications in 2020, while approximately 2.3 million neonatal deaths were recorded in 2022 (Hajji Adam and Daba, 2024). Despite global efforts under Sustainable Development Goal 3 (SDG 3), progress in reducing maternal and neonatal mortality remains uneven, with Sub-Saharan Africa bearing the highest burden.

National Context (Zimbabwe)

In Zimbabwe, maternal and neonatal health outcomes continue to be a concern. National estimates show a maternal mortality ratio of approximately 212 deaths per 100 000 live births, while a neonatal mortality rate of about 37 deaths per 1 000 live births (ZIMSTAT and ICF, 2024).

Furthermore, postnatal care utilization remains suboptimal, with many mothers failing to attend recommended postnatal visits within first six weeks after delivery (ZIMSTAT and ICF, 2024).

Local Context (Mashonaland West)

In provinces such as Mashonaland West, where Chinhoyi Provincial Hospital is located, healthcare facilities serve large populations with limited resources, contributing to high patient loads and challenges in ensuring consistent follow-up care (Ministry of Health and Child Care, 2023)

The postnatal period, particularly the first 28 days after birth, is a critical phase for both mother and newborn (World Health Organization, 2022). However, it is often neglected in practice, as many mothers are discharged within 24 to 48 hours after delivery and may not return for follow-up visits due to financial constraints, long travel distances, or lack of awareness (World Health Organization, 2022). This results in delayed detection of complications such as postpartum hemorrhage, infections, hypertensive disorders, neonatal sepsis, and feeding difficulties, which significantly contribute to maternal and neonatal morbidity and mortality (ZIMSTAT & ICF, 2024).

Traditional healthcare delivery in Zimbabwe relies heavily on face-to-face consultations and facility-based monitoring. This model limits continuity of care once patients are discharged. In resource-constrained settings, shortages of healthcare personnel and infrastructure further hinder effective postnatal monitoring (World Health Organization, 2021). These challenges highlight the need for innovative approaches that can extend care beyond healthcare facilities.

Recent advancements in artificial intelligence, particularly machine learning and deep learning, have significantly improved telehealth systems by enabling predictive analytics, pattern recognition, and early detection of complications in maternal and neonatal care. Furthermore, AI-driven models have demonstrated strong potential in neonatal intensive care settings by improving monitoring and outcome prediction (Keles and Bagci, 2023). Integrating such capabilities into telehealth platforms can enhance early diagnosis, improve clinical decision-making, and strengthen maternal and neonatal health outcomes (Vodrahalli et al., 2020).

Despite this potential, the adoption of advanced telehealth systems in Zimbabwe remains limited due to challenges such as inadequate digital infrastructure, limited access to electronic health data, and concerns related to financial constraints and implementation challenges (World Health Organization, 2021). As a result, there is a gap in the availability of intelligent, context-appropriate digital health solutions for postnatal care.

This study therefore seeks to address these challenges by designing and developing a telehealth system integrated with machine learning and deep learning techniques to enhance postnatal maternal and neonatal care at Chinhoyi Provincial Hospital. The system aims to improve remote monitoring, enable early detection of complications, and support clinical decision-making, ultimately contributing to improved health outcomes in a resource-constrained setting.

1.3 Problem statement

The core problem is that a significant proportion of postnatal mothers at Chinhoyi Provincial Hospital fail to attend recommended follow-up visits. At the national level, data indicate that postnatal care utilization remains critically low, with a substantial proportion of women not receiving recommended postnatal checks within the recommended period following delivery (ZIMSTAT & ICF, 2024). In addition, postnatal complications such as infections, hypertensive disorders, and neonatal conditions are frequently detected late, contributing to avoidable maternal and neonatal morbidity (MoHCC, 2023).

Currently, postnatal care at CPH relies primarily on facility-based visits and does not include continuous remote monitoring or advanced digital risk assessment systems. As a result, early warning signs often go unnoticed once patients are discharged, particularly among those in rural areas. While basic telehealth approaches such as phone calls and SMS reminders have been explored in similar settings, they lack the capability to analyze patterns in patient data, predict deterioration, or prioritize high-risk cases, limitations that machine learning and deep learning techniques are specifically designed to address.

Therefore, the core problem is the lack of continuous post-discharge monitoring and timely detection of postnatal complications**,** which leads to delayed interventions and preventable adverse outcomes among mothers and newborns in Mashonaland West Province.

1.4 Aim of the study

The aim of this study is to design and develop a machine learning–integrated telehealth system that supports remote postnatal monitoring, early risk prediction, and timely clinical decision-making at Chinhoyi Provincial Hospital, Zimbabwe."

1.5 specific objectives

1. To systematically survey and critically analyze existing deep learning and machine learning approaches for neonatal and maternal health risk assessment, identifying their methodological strengths, limitations, datasets used, evaluation metrics, and gaps that motivate the need for two distinct optimized models
2. To design and develop a web-based telehealth system that enables patients to input clinical data and receive real-time, actionable risk level predictions, integrated with an automated alert mechanism that notifies healthcare providers when high-risk assessments are identified.
3. To evaluate the accuracy of telehealth system using standard machine learning standard metrics including precision, recall and F1 score.

1.6 Research questions

1. What limitations in current machine learning and deep learning models for maternal and neonatal risk prediction necessitate the development of separate, task-specific predictive models for maternal health and neonatal health respectively?
2. How effectively does the web-based telehealth system enable patients to input clinical data and receive real-time, actionable risk predictions, and how usable is the system interface as measured by ease of navigation, task completion, and user satisfaction, and to what extent does the automated alert mechanism reliably notify healthcare providers within an acceptable response time when high-risk assessments are identified?
3. What is the predictive performance of the telehealth system when evaluated using standard machine learning metrics including accuracy, precision, recall, and F1 score?

1.7 Justification of the study

Significance to Maternal and Neonatal Health

This study is justified by the continued burden of maternal and neonatal morbidity and mortality during the postnatal period in-low and middle-income countries (LMICs) countries characterized by limited healthcare resources and lower income levels, such as Zimbabwe. Although progress has been made in antenatal and delivery care, the postnatal period remains inadequately addressed despite being a critical phase for both mothers and newborns (World Health Organization, 2022; World Health Organization, 2023). Delayed detection of complications such as postpartum hemorrhage, infections, hypertensive disorders, and neonatal conditions continues to contribute to preventable adverse outcomes, highlighting the need for improved postnatal monitoring and early diagnostic support.

Significance to Chinhoyi Provincial Hospital

The study is significant to Chinhoyi Provincial Hospital as it addresses challenges associated with high patient volumes, limited healthcare personnel, and constrained resources. These factors reduce the hospital's capacity to provide continuous postnatal monitoring after discharge (Ministry of Health and Child Care, 2023). By exploring a telehealth-based approach, the study seeks to improve follow-up care, enhance communication between healthcare providers and patients, and support timely identification of high-risk cases.

Significance to Postnatal Mothers and Newborns

The study is also important for postnatal mothers and newborns, particularly those in rural and underserved communities who face barriers such as long travel distances, transport costs, and limited access to healthcare services. Digital health interventions, including telehealth, have been shown to improve access to care and continuity of services through remote communication and monitoring (World Health Organization, 2021). This study aims to support early detection of complications and provide timely guidance, thereby improving health outcomes.

Significance to the Ministry of Health and Child Care

The study is relevant to the Ministry of Health and Child Care as it contributes to ongoing efforts to strengthen healthcare delivery through digital health innovations. Zimbabwe has formally committed to digital health transformation through the National Digital Health Strategy 2021-2025 (MoHCC, 2021) of which prioritize the integration of technology into healthcare delivery including maternal and postnatal services. Findings from this study may inform policy, planning, and future implementation of digital health solutions (World Health Organization, 2021; MoHCC, 2023).

Significance to Research and Knowledge

From a research perspective, existing studies on telehealth in maternal healthcare have largely focused on antenatal care, with limited attention to postnatal maternal and neonatal monitoring, particularly in-low and middle-income countries (LMICs) (Lee and Caffery, 2020; World Health Organization, 2021). This study contributes to addressing this gap by focusing on postnatal care, exploring context-specific solutions applicable to resource-constrained settings such as Zimbabwe.

1.8 Assumptions to the study

1. It is assumed that Chinhoyi Provincial Hospital has basic information and communication technology infrastructure, such as computers, mobile devices, and internet connectivity, which can support the implementation and use of a telehealth system for postnatal maternal and neonatal care.
2. The study assumes that most postnatal mothers attending Chinhoyi Provincial Hospital have access to minimum smart phones capable of supporting more advanced telehealth features such as remote communication and symptom reporting via a web-based interface.
3. Healthcare providers and mothers will participate in system evaluation if provided adequate training and support.
4. The study assumes that hospital management and healthcare workers will support the implementation and evaluation of the telehealth system, including participation in data collection, system testing, and feedback processes.

5. It is assumed that participants involved in the study, including healthcare providers and postnatal mothers, will provide honest, accurate, and reliable information during interviews, questionnaires, and system evaluations.
6. It is assumed that all data entered into the telehealth system by patients and healthcare providers is accurate, complete, and entered in good faith, and that no deliberate falsification or omission of information will occur during the study period.
7. It is assumed that ethical approval will be granted and that all data collected will be handled in accordance with ethical standards, ensuring confidentiality, privacy, and informed consent of all participants.

1.9 scope of the study

This study focuses on the development and pilot-test of the telehealth system to support postnatal maternal and neonatal care, with Chinhoyi Provincial Hospital in Mashonaland West Province, Zimbabwe serving as primary institutional site. The hospital serves as the starting point for system enrolment and clinical oversight, while the actual use of the system extends to postnatal mothers after discharge, meaning care is hospital-initiated but community-deployed for remote monitoring and follow-up support.

The study is limited to postnatal care for mothers and newborns following delivery. For mothers, the postnatal monitoring period covered by the system aligns with the WHO-defined postnatal period of up to six weeks (42 days) after birth (WHO, 2022). For newborns, monitoring focuses on the neonatal period, defined as the first 28 days of life (WHO, 2022). The study involves postnatal mothers, newborns, and healthcare professionals such as nurses, midwives, and doctors working in maternal and neonatal units. The system addresses postnatal follow-up, symptom reporting, communication, and early identification of potential complications after discharge. Antenatal care, general outpatient services, and community health programs not linked to postnatal follow-up are excluded to maintain focus and feasibility.

The telehealth system developed in this study incorporates a machine learning component to support basic risk stratification of report of reported postnatal symptom. Specifically, the system implements and optimizes established deep learning architectures, including artificial neural

networks built using TensorFlow and Keras, for the specific clinical context of maternal and neonatal risk assessment. This component was developed using the UCI Maternal Health Risk dataset sourced from the UCI Machine Learning Repository (Ahmed, 2020), which served as the primary training dataset for the maternal prediction model. For the neonatal model, a sample neonatal dataset was used as a seed, from which a clinically grounded synthetic neonatal dataset was generated using AI-assisted data augmentation techniques to supplement training. The system does not perform autonomous clinical diagnosis nor does it replace the professional judgement of healthcare providers. Rather, it functions as a decision-support tool designed to assist in the early identification of risk and to guide timely referral where necessary.

Data for the study was collected through multiple methods reflecting the mixed-methods nature of the research. Primary data was gathered from postnatal mothers and healthcare providers at Chinhoyi Provincial Hospital through questionnaires. The maternal machine learning model was trained on the UCI Maternal Health Risk dataset obtained from the UCI Machine Learning Repository. For the neonatal model, a sample neonatal dataset was used as a foundation, and a clinically grounded synthetic neonatal dataset was generated using AI-assisted augmentation to provide sufficient training data. Additional secondary data was drawn from peer-reviewed literature on maternal health and digital health systems.

1.10 Technical and Ethical consideration

Data security and privacy

The system will implement appropriate data protection measures to safeguard sensitive patient information. Data collection will follow a data minimization principle, where only essential clinical information required for postnatal risk assessment such as age, temperature, and blood pressure is collected. Non-essential personal details (e.g., marital status, HIV status) will not be requested, thereby reducing privacy risks.

All data transmitted between users and the system will be encrypted using secure communication protocols (HTTPS) to prevent unauthorized interception. Patient data will be stored in a secure MySQL database, with additional protection measures such as SHA-256 cryptographic hashing

algorithm to prevent unauthorized access. Access to the system will be restricted to authorized healthcare personnel through secure authentication mechanisms.

Given the infrastructure realities of Chinhoyi Provincial Hospital and Mashonaland West Province, including intermittent power supply, load shedding, and inconsistent internet connectivity, the database will be hosted on a dedicated local hospital server as the primary deployment environment. Cloud-based backup storage will be implemented as a secondary measure to prevent data loss and support system recovery in the event of hardware failure. This approach ensures system availability during network outages, reduces dependency on continuous internet access, and aligns with Zimbabwe's data sovereignty considerations under the Data Protection Act [Chapter 11:12]. The study will adhere to Zimbabwe's Data Protection Act [Chapter 11:12] and relevant health data confidentiality guidelines from the Ministry of Health and Child Care.

Algorithmic fairness and Bias mitigation

Considering the utilization of predictive methodologies such as machine learning, steps will be taken to counteract any possible biases when predicting risks. For example, the information to be used in the research process will be sourced from various healthcare facilities. Specifically, the maternal model was trained on the UCI Maternal Health Risk dataset from the UCI Machine Learning Repository, and the neonatal model utilized a synthetically generated dataset derived from a sample neonatal dataset using AI-assisted augmentation techniques. This will ensure that a wide range of patient samples are used, thus reducing the chances of any possible biases due to an insufficient sample size**.**

The accuracy of the system will be tested in various demographic groups. The demographic groups will include different age ranges and patients who have varying geographic backgrounds (i.e., urban vs. rural). Discrepancies in the performance of the system among these demographic groups will be addressed using mitigation techniques. These may include data balancing, adjustments to the models, or refining the decision rules used by the algorithm.

It should be noted that a human-in-the-loop design will also be adopted in this scenario. In essence, clinicians will be required to evaluate and confirm the risk predictions made by the system. This will help identify any possible biases or inaccuracies and address them accordingly.

Clinical oversight and responsibility

The telehealth system is designed strictly as a decision-support tool and does not replace clinical judgment. Final diagnostic authority and treatment decisions remain the responsibility of qualified healthcare professionals, including doctors, nurses, and midwives. The system will provide risk indicators and alerts to support early detection of potential complications, but all clinical actions will be validated and executed by healthcare providers. This ensures clear accountability and reduces the risk of over-reliance on automated outputs.

Sustainability Plan

Integration pathway: Upon successful validation, results and a deployment framework will be presented to the local hospital administration and the Zimbabwe Ministry of Health and Child Care.

Budget transition: A cost-analysis of maintaining the system (server, minimal technical support, updates) will be provided to facilitate potential inclusion in hospital or district health budgets.

1.11 chapter summary

This chapter presented an overview of the study on the development of a telehealth system for enhanced postnatal maternal and neonatal care at Chinhoyi Provincial Hospital by outlining the background, problem, and purpose of the research. It examined global, regional, and local challenges associated with postnatal maternal and neonatal care, highlighting persistent gaps in follow-up, monitoring, and early detection of complications, particularly within resource-constrained provincial hospital settings in Zimbabwe. The chapter identified specific limitations in existing postnatal care approaches at Chinhoyi Provincial Hospital and presented the aim, objectives, and research questions guiding the design, development, and evaluation of a context-appropriate telehealth system. It further defined the scope of the study and justified its significance

to the hospital, postnatal mothers and newborns, the community, the Ministry of Health and Child Care, and the broader research field. Overall, the chapter established the rationale for the study and laid the foundation for subsequent chapters, which address the literature review, research methodology, system design, results, and discussion of findings.

1.12 definition of terms

Telehealth is the use of information and communication technologies to deliver healthcare services remotely, including consultation, monitoring, communication, and health education between healthcare providers and patients.

Maternal Care is the service provided to women during pregnancy, childbirth, and the postnatal period to ensure the health and well-being of the mother.

Neonatal Care is the service provided to newborn infants, typically within the first 28 days of life, focusing on monitoring growth, development, and early detection of health complications.

Postnatal Care are the services provided to mothers and newborns after childbirth, aimed at monitoring recovery, identifying complications, and promoting healthy practices.

Postnatal Diagnostic Support is the use of digital tools and clinical guidance to assist healthcare providers in identifying potential maternal and neonatal health complications during the postnatal period.

Enhanced Care refers to an improved model of postnatal support that extends beyond the traditional boundaries of hospital-based clinical visits by integrating digital technology to deliver continuous, accessible, and responsive follow-up to mothers and newborns after discharge.

Remote Monitoring is the collection and transmission of health-related data from patients to healthcare providers using digital devices without requiring physical visits to healthcare facilities.

Neonate is a newborn infant from birth up to 28 days of life.

Machine learning is a branch of Artificial Intelligence that enables compute systems to learn from data and improve their performance on a task without being explicitly programmed.

MHealth is the use of mobile devices such as smartphones, tablets and wearables technologies to support medical and public health practices.

EHealth is the use of digital technologies and electronic systems to deliver, manage and improve healthcare services.

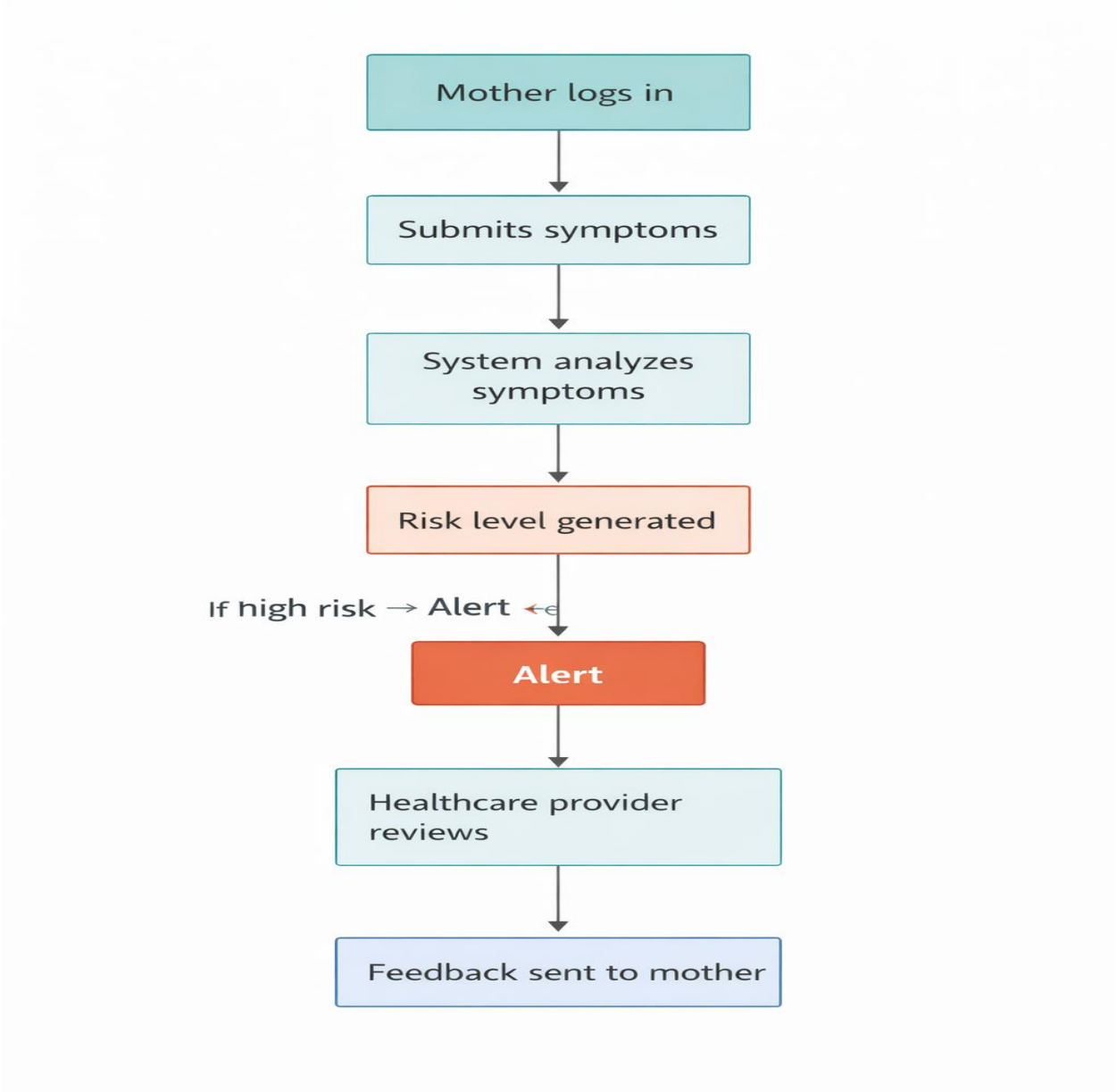


Figure 1: System Flow Diagram

Chapter 2

2.1 Background

Maternal and neonatal health remains a critical global priority, reflecting both population well-being and the strength of healthcare systems. Despite significant medical advancements, preventable mortality persists, with approximately 300 000 maternal deaths reported globally in 2020, the majority occurring in low- and middle-income countries and largely due to complications such as hemorrhage, hypertensive disorders, and sepsis (Musarandega et al., 2021). Similarly, neonatal mortality continues to represent a substantial proportion of under-five deaths, with prematurity, birth asphyxia, and infections identified as leading causes (Boerma et al., 2023; Sharrow et al., 2022).

These global disparities are particularly pronounced in Sub-Sahara Africa, where structural health system weaknesses compound clinical vulnerabilities (Kassa et al., 2024). In Zimbabwe specifically, national estimates place the maternal mortality ratio at approximately most recent 2023-24 Zimbabwe Demographic and Health Survey recorded 212 deaths per 100 000 live births, representing a significant decline from 651 per 100 000 recorded in the 2015 survey (Zimbabwe National Statistic Agency (ZIMSTAT) & ICF, 2024). Critically, this progress in maternal mortality increase from 29 to 37 deaths per 1 000 live births between the 2015 and 2023-24 surveys a 28% rise while infant mortality worsened from 50 to 56 deaths per 1 000 live births over the same period (ZIMSTAT & ICF, 2024). These diverging trajectories reveal a structural gap in the continuum of perinatal care that extends beyond facility-based delivery into the postnatal period, where monitoring and follow-up remain least reliable (Galle et al., 2023).

Beyond mortality, the quality of care during the antenatal, intrapartum, and postnatal periods is a determinant of lifelong health. Barriers to optimal care include geographical isolation, workforce shortages, socioeconomic disparities, and fragmented care pathways that hinder continuity between hospital and community settings. The traditional model of in-person, episodic care is often insufficient to provide the continuous monitoring, timely diagnosis, and psychosocial support required for this vulnerable population. These challenges necessitate the exploration of innovative, scalable, and patient-centered service delivery models.

2.1.2 The emergency of Telehealth in Perinatal care

The adoption of telehealth has significantly changed healthcare delivery by enabling patients to access medical services remotely through digital technologies, including computers, mobile devices, and wearable sensor (Sikka et al., 2021). Its application in maternal and neonatal care has gained unprecedented momentum, particularly following the COVID-19 pandemic, which necessitated a rapid shift from traditional face-to-face consultations to virtual healthcare delivery models (Peahl et al., 2021). In low-resource settings such as Zimbabwe, the pandemic exposed significant challenges within healthcare systems, including shortages of healthcare professionals, limited access to maternal healthcare facilities and movement restrictions that affected postnatal follow-up services. As a result, telehealth became an important alternative for ensuring continuity of care for mothers and newborns while reducing unnecessary hospital visits and minimizing the risk of infection transmission.

Telehealth in perinatal care encompasses several modalities that support maternal and neonatal healthcare delivery. The simplest form is synchronous care, which involves real-time communication between healthcare providers and patients through video conferencing or telephone consultations for antenatal care, lactation support and postpartum follow-up. Another modality is asynchronous or store-and-forward care, where clinical information such as blood pressure readings, blood glucose records, or images of neonatal conditions can be transmitted electronically to healthcare professionals for later assessment. More advanced approaches include remote patient monitoring (RPM), which utilizes wearable sensors and digital monitoring devices to continuously track physiological parameters and facilitates the early detection of complications such as preeclampsia, postpartum hypertension. The adoption of such technologies have the potential to transform healthcare accessibility, mitigating unnecessary facility visits, enhance early diagnosis and empower mothers to participate actively in their own healthcare management.

This literature review therefore examines the emergence of telehealth technologies in maternal and postnatal healthcare, the integration of machine learning techniques in remote health monitoring, and the challenges and opportunities associated with implementing telehealth systems in resource-constrained healthcare environments such as Zimbabwe.

2.2 Relevant theory of the subject matter

Theoretical Frameworks

To critically evaluate and synthesize the literature on telehealth systems for maternal and neonatal care, it is essential to establish a theoretical foundation. Theoretical frameworks provide a lens through which to understand the mechanisms of intervention effectiveness, the complex interactions between technology, patients, providers, and the healthcare system, and the factors that influence adoption and sustained use. This section outlines the key theories and models that underpin the analysis in this review.

2.2.1 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), is a theoretical framework for understanding user acceptance of information systems positing two major constructs: perceived usefulness and perceived ease of use. TAM is a direct precursor of UTAUT which has been developed in part to address the two constructs of TAM and adds social influence and facilitating conditions, and also provides moderating variables (age, gender and experience), leading to an improved explanation of adoption behavior (Tamilmani et al., 2021; Venkatesh et al., 2003).

Performance expectancy refers to the degree to which an individual believes that using the system will help them attain gains in job performances or, in the case of patients, improved health outcomes. In maternal telehealth, this translate to whether clinicians believe remote monitoring improves clinical decision- making and whether postnatal mothers believe virtual consultations lead to better pregnancy outcomes (Thanthrige et al., 2025). Effort expectancy concerns the perceived ease of use of the system, requiring telehealth platforms be intuitive and demand minimal cognitive and physical effort for postpartum women recovering from childbirth or managing newborn; for providers, seamless integration into existing workflow is equally critical (Kruse and Heinemann, 2022). Facilitating conditions refers to the presence of organizational and technical infrastructure supporting system use, including reliable internet connectivity, access to appropriate devices, availability of technical support and reimbursement policies, factors consistently identified as key determines of telehealth adoption (Rouidi et al., 2022). Social

influence reflects the degree to which an individual perceives peer clinicians, hospital management and community health norms.

The UTAUT framework also considers finding moderating variables such as age, gender, experience and voluntariness of use that manifests itself in a variety of technology adoption behavior from different user groups. This framework was particularly useful during the study on the adoption and acceptability of a machine learning- enhanced telehealth system form remote postnatal monitoring at Chinhoyi Provincial Hospital.

UTAUT Construct	**Meaning**	**Application to ML Telehealth at Chinhoyi Provincial Hospital**
Performance expectancy	Belief that using the system improves job performance or health outcomes	Clinicians confidence that ML-driven risk alert improve early detection of postnatal complications, mothers belief that virtual follow-ups lead to better recovery outcomes
Effort expectancy	Perceived ease of use of the system	Ease with which postnatal mothers and nurses interact with the telehealth interface, minimal training burden for clinical staff at Chinhoyi
Social influence	Perception that important others support system use	Healthcare workers encourage adoption among staff and patients
Facilitating conditions	Organizational and technical infrastructure supporting use	Availability of smartphones or clinical devices, reliable internet connectivity on Chinhoyi, technical support and institutional policies enabling telehealth reimbursement

Table 2.2.1: The Unified Theory of Acceptance and Use of Technology

2.2.3 Technology Acceptance Model

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), provides a foundational framework for examining user acceptance of information systems, emphasizing two primary constructs: perceived usefulness and perceived ease of use. TAM serves as a direct predecessor to UTAUT, which was developed partly in response to TAMs two constructs by incorporating social influence and facilitating conditions and introduces moderating variables such as age, gender and experience, offering a more comprehensive account of adoption behavior. Despite this evolution, TAM remains widely applied in health technology research for its parsimony and its ability to isolate the specific role of user perceptions in adoption decisions.

(Liu et al., 2022) highlighted that perceived usefulness significantly affects the adoption of mobile health services, particularly when users believe that the system will improve their health outcomes and enhance performance, while perceive ease of use reduces the effort required to engage with the technology, thereby promoting continuity use. Similarly, (Rouidi et al., 2022) demonstrated that facilitating conditions, such as, reliable technical infrastructure and organizational support, strongly influence healthcare professionals willingness to adopt telemedicine systems. In the context of maternal and neonatal care, (Atkinson et al., 2023) reported that telehealth interventions, including antenatal programs are likely to be accepted when they deliver contextually relevant, culturally approach health information and integrate support from healthcare provides.

Collectively, these studies illustrate that the success of telehealth adoption depends not only on the design and usability of the technology but also on the surrounding support structure, user perception and integration into existing care pathways. Nevertheless, TAM has attracted criticism for its theoretical simplicity. The emphasis of TAMs on perceived usefulness and ease of use does not sufficiently explain the complexity of healthcare situations, as this model often neglects key factors including trust cultural diversity and domain-specific issues like regulatory restriction and decision-making processes (Dhagarra et al., 2020; Zoccarato et al., 2024). In the context of postnatal telehealth at Chinhoyi Provincial Hospital, TAM offers a useful but partial lens, most valuable for understanding individual-level acceptance among clinicians and patients, but

insufficient in its own to account for the systemic and infrastructure that govern implementation feasibility.

2.2.4 The Digital Health Equity Framework

Given persistent disparities in maternal and neonatal outcomes by race, ethnicity, socioeconomic status, and geography, this review applies the Digital Health Equity Framework, which emphasizes that digital health interventions can either reduce or exacerbate existing health inequities depending on their design and implementation (Crawford and Serhal, 2020). A primary consideration within this framework is access, which encompasses differential availability of broadband internet, smartphones, and digital literacy skills across populations. (Sieck et al., 2021) highlighted that inequities in digital infrastructure and technology access disproportionately affect rural, low-income, and marginalized communities, reinforcing existing health disparities.

Algorithmic bias is another critical concern, as diagnostic tools and predictive algorithms may perform differently across populations, potentially leading to unequal outcomes. Machine learning models are only as equitable as the data on which they are trained; when training datasets underrepresent certain racial, ethnic, or socioeconomic groups, as is frequently the case with datasets drawn from high-income country health systems. In a low-resource Zimbabwean context, where postnatal data infrastructure is limited and populations may differ substantially from those represented in existing maternal health datasets, the risk of algorithmic bias generating inequitable clinical outcomes is therefore not merely theoretical but a concrete implementation challenge that must be proactively addressed through locally representative training data and ongoing model auditing.

Finally, trust represents a foundational element, shaped by historical and systemic factors, including legacies of medical racism and current experiences of discrimination within healthcare systems. (Richardson et al., 2022) emphasized that cultivating trust and engaging communities meaningfully are essential for equitable adoption and sustained use of digital health technologies. Collectively, these considerations underscore that promoting equity in digital maternal and neonatal health requires deliberate attention to infrastructure, algorithmic fairness, and community trust, that a machine learning-based postnatal system. However, technically sophisticated, will

only achieve equitable impact if these dimensions are embedded into its design, validation, and governance from the outset.

2.3 Empirical Evidence

2.3.1 Antenatal Telehealth Interventions

(Reisinger-Kindle et al., 2021) published a mixed-methods evaluation of the rapid implementation of telehealth for prenatal and postpartum care visits during the COVID-19 pandemic in an academic health system in the United States, highlighting challenges and facilitators experienced by patients and clinicians. The study analyzed visit data from over 15,000 patients and conducted 45 semi-structured interviews with clinicians and staff. Quantitative findings revealed that telehealth accounted for 58% of all prenatal visits at the peak of the pandemic, with no significant increase in adverse outcomes. Qualitative analysis identified key implementation facilitators, including institutional leadership support and pre-existing technology infrastructure, alongside barriers such as inconsistent state-level reimbursement policies and challenges in performing physical assessments virtually. These findings suggested that rapid telehealth scale-up in antenatal care is feasible when institutional conditional conditions are enabling, but that reimbursement policy and physical examination limitations represent persistent structural constraints that technology alone cannot resolve.

(DeNicola et al., 2020) conducted a systematic review evaluating the effectiveness of telehealth interventions in obstetric and gynecologic care, analyzing 47 studies involving over 31 000 participants across various modalities including mobile health applications, remote monitoring and virtual consultations. Their findings indicated that telehealth interventions can improve health outcomes, including increased access to care, better health behaviors and clinical outcomes broadly comparable to traditional in-person care. However, (DeNicola et al., 2020) noted considerable variability in study quality and emphasized the need for more rigorous and standardized research, particularly in high-risk obstetric populations.

The empirical literature on antenatal telehealth from sub-Saharan Africa remains notably sparse. (Kachimanga et al., 2024) found that while community health worker-delivered mHealth programs show promise for improving antenatal care uptake, significant heterogeneity across sociotechnical contexts limits the generalizability of findings. Despite over 515 million mobile phone subscriptions across the region, few countries have fully transitioned from paper-based to

electronic health systems and Zimbabwe specific evaluations with robust outcome data remain largely absent from the published literature (Olomi et al., 2025). This evidence gap compounded by digital access inequities, infrastructure constraints and limitations of virtual physical assessment, underscores the need for locally validated, contextual adapted implementation approach at Chinhoyi Provincial Hospital.

2.3.2 Postnatal telehealth

(Hoppe et al., 2020) evaluated a telehealth program with remote blood pressure monitoring for postpartum patients with hypertensive disorders of pregnancy, published in the *American Journal of Obstetrics and Gynecology*. In this non-randomized controlled trial involved 428 women, the intervention group received Bluetooth- enabled blood pressure cuffs, specifically the iHealth Track BP5 upper arm monitor, which transmits readings wirelessly to a paired tablet or smartphone alongside tablets configured for daily transmission of vitals to a central database, with trained nurses utilizing a standardized algorithm to guide antihypertensive management. The study found that the telehealth group had significantly fewer hypertension-related readmissions compared to the standard care group (0.5% vs 3.7%; adjusted RR 0.12, 95% CI 0.01-0.96). Furthermore, 94.4% of women in the intervention group had at least one blood pressure measurement reviewed within ten days of delivery, compared to 60.3% in the control group. The study underscore the potential of remote patient monitoring to bridge the critical gap between hospital discharge and the standard postpartum follow-up period.

(Uscher-Pines et al., 2025) examined the use of telehealth-based lactation support delivery through video consultation shortly after hospital discharge. The study found that virtual access to lactation consultants improved breastfeeding outcomes, including higher rates of initiation and continuation. The intervention was particularly beneficial for mothers requiring additional support, such as, first-time mothers. The authors also emphasized that reimbursement policies and insurance coverage are important factors influencing the sustainability and scalability of telehealth lactation services, noting that without sustainable funding mechanisms, even clinically effective telehealth programs risk discontinuation following initial implementation.

Both studies provide compelling evidence that postnatal telehealth interventions can meaningfully improve maternal outcomes in the immediate post-discharge period. However, both were conducted in high-resource United States settings where reliable broadband connectivity,

smartphones ownership, insurance reimbursement and well-resourced nursing workforces are broadly assumed of conditions that cannot be taken for granted at Chinhoyi hospital. Intermittent internet connectivity, limited patient device ownership, and constrained staffing ratios present substantively different implementation challenges. The Bluetooth-enabled blood pressure devices used by Hoppe et al. (2020), while effective in a connected urban setting, require careful evaluation for low-resource contexts where device cost, battery dependence, and absent Wi-Fi coverage may necessitate lower-cost alternatives such as the validated OMRON M2. Fewer than 10% of households in sub-Saharan Africa own a validated blood pressure monitor compared to over 60% in high-income countries, with retail prices frequently exceeding a week's income for many families, rendering patient-owned device models largely unfeasible without institutional procurement strategies (Tesfaye Hailu and Mekonnen Duguma, 2025). These contextual disparities reinforce the need for locally adapted telehealth models rather than direct replication of high-income country protocols.

2.3.3 Neonatal Diagnosis

(Ngeow et al., 2024) evaluated a smartphone-based machine learning application for neonatal jaundice screening in a prospective diagnostic study involving 546 neonates, using total serum bilirubin as the reference standard. The app demonstrated excellent sensitivity and good specificity for detecting clinically significant hyperbilirubinemia, with some variation across subgroups, highlighting both its potential clinical utility and the need for further validation in diverse populations (Ngeow et al., 2024).

Machine learning has demonstrated promising diagnostic performance across neonatal clinical domains directly relevant to the proposed Chinhoyi system. For jaundice screening, smartphone-based ML applications have shown strong sensitivity for detecting clinically significant hyperbilirubinemia, offering a low-cost, non-invasive alternative suited to settings with limited laboratory infrastructure (Ngeow et al., 2024; Taylor et al., 2017). For sepsis detection, a leading cause of neonatal mortality in low-resource settings, vital sign-based ML algorithms provide clinically useful predictive value, and a scoping review confirmed that ML can guide antibiotic treatment decisions, a critical finding given that over 70% of neonatal bloodstream infections resist first-line antibiotics (Honoré et al., 2023; O’Sullivan et al., 2023). Zimbabwe-specific evidence directly supports feasibility: a LightGBM classifier trained on Neotree data from Sally Mugabe

Central Hospital achieved an AUC of 0.712 for early-onset sepsis prediction (Gannon et al., 2024a), while Neotree data from Chinhoyi Provincial Hospital itself revealed that clinical sepsis features were frequently not acted upon and antibiotic prescription rates fell below WHO recommendations, directly underscoring the need for ML-enhanced decision support at this site (Khan et al., 2025). While these findings confirm ML-based neonatal tools are both technically feasible and clinically relevant, most models were developed in well-resourced settings, reinforcing the need for local model training, validation, and ongoing performance auditing.

2.4 Implementation and contextual evidence

2.4.1 Technology Acceptance

Recent studies on technology acceptance emphasize the need to extend traditional models to better account for the diverse factors that influence the adoption of digital health technologies. The extended Unified Theory of Acceptance and Use of Technology (UTAUT2) enhances the original framework by incorporating additional factors such as hedonic motivation, price value, and habit, thereby providing a deeper understanding of users' willingness to adopt and continuously use technology. (Tamilmani et al., 2021). These constructs are particularly relevant in maternal telehealth contexts, where engagement depends not only on perceived usefulness but also on the enjoyment of using the system, the perceived value relative to costs, and the establishment of habitual use. By integrating these broader determinants, UTAUT2 offers a comprehensive lens to examine the multifaceted drivers of both patient and provider adoption of telehealth systems in perinatal care, allowing researchers and practitioners to better understand and support sustained digital health engagement.

(Mackworth-Young et al., 2024) applied the RE-AIM framework to evaluate the feasibility, adoption and implementation of a mobile phone-based intervention aimed at improving healthcare service utilization among young people in Chitungwiza, Zimbabwe. Their findings demonstrated both the feasibility of digital health interventions and the implementation challenges associated with deploying such systems in high-burden healthcare environments. Similarly, (Gannon et al., 2024) assessed the development and usability of digital diagnostic algorithms for neonatal units in Zimbabwe, illustrated how digital tools can be integrated into newborn healthcare pathways while also highlighting practical implementation considerations within hospitals settings. Furthermore,

population-level analyses by (Mbunge et al., 2023) found that access to digital technologies was associated with antenatal care visits patterns in Zimbabwe, suggesting that digital connectivity significantly influences maternal healthcare utilization.

These findings demonstrate that implementation and translational evaluation frameworks are increasingly relevant for assessing digital health and telemedicine interventions in Zimbabwe, where infrastructural, economic, and social determinants strongly influence the uptake and sustainability of technology-mediated healthcare services. While these Zimbabwean studies provide valuable contextual evidence, most of them focus primarily on urban or peri-urban environments such as Chitungwiza and larger referral healthcare institutions. In contrast, Chinhoyi Provincial Hospital serves a broader semi-urban and rural population, where additional challenges such as unstable internet connectivity, limited access to smart devices, digital illiteracy, and shortages of healthcare personnel may further affect telehealth implementation and adoption. This highlights the importance of evaluating machine learning-enhanced telehealth systems within resource-constrained and underserved maternal healthcare settings to ensure that proposed solutions are both contextually appropriate and sustainable.

2.4.2 Health Equity

(Crawford and Serhal, 2020), in *JMIR Mental Health*, proposed the Digital Health Equity Framework as a response to growing concerns that digital health innovations may inadvertently widen health disparities. The framework outlines four domains for equity-oriented digital health design: (1) access and infrastructure, (2) usability and digital literacy, (3) cultural appropriateness and representation, and (4) trust and privacy. This theoretical contribution is essential for this review, as it provides a critical lens through which to evaluate whether telehealth studies in maternal and neonatal care adequately address the needs of diverse populations and report outcomes disaggregated by relevant social determinants (Crawford and Serhal, 2020).

(Kim and Backonja, 2025) conducted a scoping review to systematically examine how digital health equity has been conceptualized across published frameworks and to identify key concepts that inform equitable digital health intervention development, implementation, and evaluation. Their review highlighted that while many frameworks exist, none fully capture the range of factors that shape digital health equity, and they identified hundreds of equity-related concepts spanning individual, community, organizational, and societal levels. Central themes included access to digital health services, the value and impact of interventions on end users, partnerships, and broader contextual determinants such as digital literacy and digital inclusion. Based on this synthesis, Kim & Backonja proposed a consolidated definition of digital health equity and outlined core elements that researchers and practitioners should consider when designing and assessing digital health initiatives. This work provides a comprehensive foundation for advancing digital health equity by clarifying concepts and suggesting how frameworks

can be strengthened to guide equitable innovation, including in areas like telehealth for underserved populations.

The Digital Health Equity Framework is particularly applicable to this study at Chinhoyi Provincial Hospital because the proposed machine learning-enhanced telehealth system seeks to address several equity-related challenges affecting postnatal healthcare delivery in Zimbabwe. In terms of access and infrastructure, the system aims t support remote healthcare delivery for mothers in underserved and rural communities who may experience difficulties accessing healthcare facilities. Regarding usability and digital literacy, the proposed platform is intended to provide a simple and user-friendly interface that minimizes technical complexity for both postnatal mothers and healthcare workers. Cultural appropriateness and representation are addressed through the consideration of local maternal healthcare needs contextual healthcare challenges within Zimbabwean healthcare settings. Finally, trust and privacy are important considerations for ensuring secure handling of patient information and promoting user confidence in the telehealth platform. By incorporating these equity-oriented principles, the study seeks to support inclusive, accessible, and sustainable digital maternal healthcare services within resource-constrained healthcare environments.

2.4.3 Perinatal care transformation

(Guendelman et al., 2023), writing in *Telemedicine and e-Health*, explored factors influencing telehealth use among practicing maternal-fetal medicine clinicians, identifying key domains related to clinical integration, technological infrastructure, and organizational readiness that affect sustainable telehealth adoption. Drawing on implementation science principles, their findings emphasize the importance of aligning virtual care with clinical workflows, ensuring reliable technology and connectivity, and addressing financial and policy considerations to support lasting integration of telehealth in perinatal care. These determinants are not isolated technical considerations but are deeply interconnected: even well-designed telehealth platforms fail to achieve sustained adoption when organizational readiness is low or when reimbursement structures do not support virtual care delivery (Guendelman et al., 2023).

These findings carry direct implications for the integration of machine learning into maternal-fetal medicine. ML-based clinical decision-support tools, such as automated fetal heart rate classifiers or preeclampsia risk prediction models which are typically embedded within existing telehealth infrastructures and therefore inherit the same adoption barriers (Guendelman et al., 2023) identify. Clinician trust in algorithmic outputs, the interoperability of ML systems with clinical workflows, and the availability of connectivity sufficient to support real-time data processing represent additional layers of implementation complexity that extend beyond conventional telehealth adoption. Addressing these challenges requires that ML integration be treated not as a purely

technical undertaking but as an organizational and implementation science challenge, one that demands the same deliberate attention to workflow alignment, stakeholder engagement, and policy enablement that (Guendelman et al., 2023) identify as foundational to sustainable telehealth adoption in perinatal care.

2.5. Deep Learning

Deep learning (DL), a specialized branch of machine learning, utilizes multiple layers of non-linear processing units to automatically extract complex features from data and identify patterns for classification tasks (Deng, 2014). DL is adopted in computer-assisted medical diagnosis (Lin et al., 2016). In medical image analysis, DL applications include classification, segmentation, detection, retrieval and registration of images. Beyond imaging, deep learning architectures, particularly Artificial Neural Networks (ANNs), have demonstrated strong performance in structured clinical tabular data tasks such as risk stratification and outcome prediction, making them well suited to the classification problem addressed in this study.

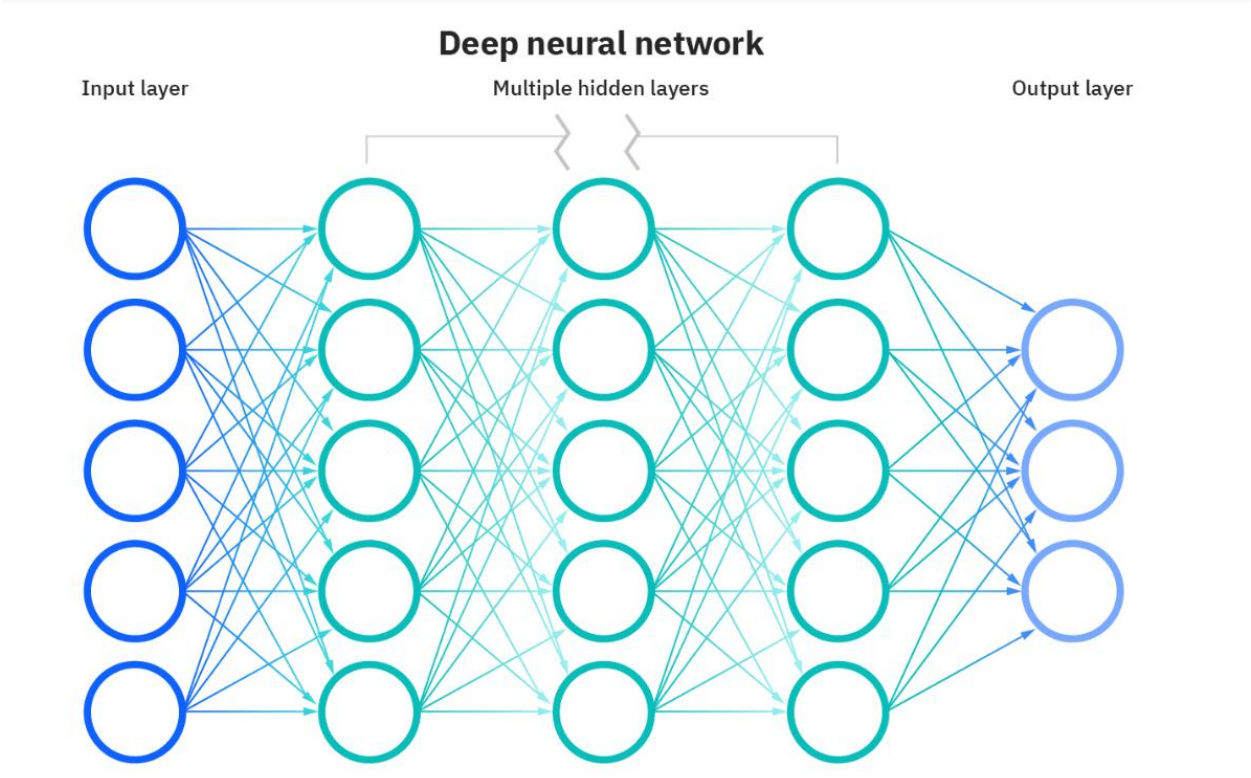


Figure 2: Deep neural network

The figure demonstrates how information flows from the input layer through multiple hidden layers, where increasingly abstract feature combinations are learned, before producing a final

classification at the output layer. In this study, the input layer receives the clinical indicators, the hidden layers learn the complex interactions between those variables, and the output layer produces the three-class risk probability distribution described above.

2.6 Chapter summary

2.6.1 Gaps in the Literature

Lack of context-specific research in Zimbabwe postnatal care

Most existing telehealth and machine learning studies in maternal and neonatal healthcare have been conducted in high-income countries such as the United States and United Kingdom, where healthcare infrastructure, internet connectivity, digital literacy and access to smart devices are significantly more advanced. Although some Zimbabwe studies have explored digital health interventions, they have primarily focused on urban or peri-urban settings such as Chitungwiza and larger referral hospital. There remains limited empirical evidence on the implementation of machine learning-enhanced telehealth systems within semi-urban and resource-constraints healthcare settings such as Chinhoyi Provincial Hospital. This study directly addresses this gap by designing and evaluating a contextual adapted telehealth system specifically for postnatal monitoring within Zimbabwe provincial hospital setting.

Limited integration machine learning in postnatal telehealth systems

Existing telehealth studies largely focus on virtual consultations, remote monitoring and communication platforms without incorporating intelligent clinical decision-support mechanisms. While machine learning applications have shown promising results in neonatal diagnosis and risk prediction, few studies have integrated machine learning into postnatal telehealth systems for early detection of maternal and neonatal complications. Furthermore, most machine learning models have been trained using datasets from high-income countries, raising concerns regarding contextual relevance and algorithmic bias in African healthcare environments. This study addresses this gap by proposing a machine learning-enhanced telehealth system capable of supporting remote postnatal monitoring and early diagnostic support using contextually relevant healthcare considerations.

Insufficient focus on postnatal care compared to antenatal care

The literature demonstrates that telehealth research has predominantly concentrated on antenatal care interventions, with comparatively limited attention given to postnatal period. However, the postnatal phase remains one of the most vulnerable stages for both mothers and newborns, particularly in low-resource settings where follow-up care is inconsistent. Existing studies acknowledge that postnatal monitoring gaps contribute significantly to preventable maternal and

neonatal complications, yet there remains limited research scalable digital systems specifically designed for continuous postnatal monitoring in Zimbabwe. This study addresses this gap by focusing specifically on postnatal healthcare delivery and remote monitoring after hospital discharge.

Limited research on equity-oriented digital health implementation

Although digital health equity frameworks emphasize issues such as accessibility, digital literacy, cultural appropriateness, trust and infrastructure, many telehealth studies inadequately address how these factors influence implementation in underserved populations. In low-resource settings such as Zimbabwe, barriers including unstable internet connectivity, limited smartphones access and low digital literacy may significantly affect telehealth adoption and sustainability. This study addresses this gap by incorporating equity-oriented design considerations into the proposed telehealth system to improve accessibility, usability and contextual appropriateness for postnatal mothers and healthcare workers.

Lack of locally validated implementation framework for maternal telehealth

Current implementing evidence highlights that successful telehealth adoption depends on organizational readiness, infrastructure availability, healthcare worker acceptance and integration into clinical workflows. However, there remains limited research evaluating how technology acceptance frameworks such as UTAUT and Digital Health Equity frameworks apply specifically to machine learning-enhanced maternal telehealth systems in Zimbabwe provincial healthcare institutions. This study addresses this gap by evaluating the implementation considerations adoption factors and contextual challenges associated with deploying a telehealth system at Chinhoyi Provincial Hospital.

Summary of the research gap

Overall, the literature demonstrates increasing interest in telehealth, machine learning and digital maternal healthcare. However, there are remains a significant gap in contextual-specific, equity-oriented and machine learning-enhanced postnatal telehealth research within resource-constrained healthcare settings in Zimbabwe. This study therefore contributes to the existing body of knowledge by designing and evaluating a machine learning-enhanced telehealth system tailored to the operational realities and maternal healthcare needs of Chinhoyi Provincial Hospital.

2.6.2 Notable challenges

1. Technical barrier, including limited device availability, unstable internet connectivity and low levels of digital literacy among patients and healthcare providers.
2. Policy, regulatory and reimbursement inconsistencies that may affect the adoption, scalability and sustainability of telehealth services.
3. Algorithmic bias and the need for culturally sensitive, trust-building interventions to ensure equitable and inclusive healthcare delivery.
4. Maintaining continuity of care while ensuring patient data privacy, confidentiality and cybersecurity within digital health platforms.
5. Integration of machine learning algorithms within resource-constrained healthcare environment characterized by limited local technical expertise, inadequate digital infrastructure and challenges in maintaining and validating intelligent healthcare systems.

2.6.3 Implications for practice and policy

The findings of this review carry important implications for clinical practice and healthcare policy. For healthcare providers, including doctors and nurses, as well as healthcare institutions, the evidence supports the integration of the telehealth as a complimentary healthcare delivery modality rather than a complete replacement for in-person care. Hybrid care models that combine virtual consultations with physical visits may provide the optimal balance between accessibility, continuity of care and clinical safety. Furthermore, successful implementation of telehealth systems requires the establishment of clear protocols for patient monitoring, alert management and technical support to ensure timely clinical intervention and safe healthcare delivery.

For policymakers, this review highlights the need for sustainable reimbursement and regulatory frameworks that recognize the value of telehealth services across the maternal and neonatal healthcare continuum. Inconsistent reimbursement policies have been identified as a major barrier affecting the adoption and long term sustainability of telehealth interventions (Reisinger-Kindle et al., 2021). The review also highlights the importance of investing in broadband infrastructure, digital literacy programs and affordable access to digital technologies in order to improve equitable access to telehealth services, particularly for rural and undeserved.

The implications are particularly relevant within the context of Zimbabwe, where national digital health transformation initiatives increasingly recognize the importance of integrating information and communication technologies into healthcare delivery. Zimbabwe's national eHealth and Digital Health strategies emphasize the strengthening of health information systems, telemedicine services, electronic health records and digital infrastructure to improve healthcare accessibility and efficiency. However, existing implementation challenges such as inadequate infrastructure, workforce limitations, fragmented digital systems and unequal access to digital technologies contribute to affect the scalability and sustainability of digital health interventions.

2.6.4 Conclusion

Telehealth systems for maternal and neonatal care represents a transformative opportunity to enhance healthcare delivery and improve postnatal diagnosis and monitoring. The evidence reviewed demonstrates meaningful benefits across the perinatal continuum, including antenatal monitoring, postpartum support, remote patient monitoring and neonatal screening. However, the successful and equitable integration of these technologies into routine healthcare practice requires a deliberate and evidence-informed approach that addresses persistent knowledge gaps while carefully considering implementation contexts, infrastructural limitations, healthcare workforce readiness and digital health equity concerns.

As digital health technologies continue to evolve, the priority should not simply be the adoption of telehealth for its own sake, but rather its strategic deployment to advance the fundamental goals of maternal and neonatal healthcare: safe, accessible, continuous, patient-centered and compassionate care for every mother and newborn. Achieving this vision will require sustained collaboration among researchers, healthcare professionals, policymakers, technology developers and local communities to ensure that telehealth technologies improve healthcare outcomes without further marginalizing vulnerable populations.

In the context of Chinhoyi Provincial Hospital, the reviewed literature highlights the need for contextually adapted and sustainable digital solutions capable of addressing the challenges associate with postnatal follow-up, healthcare accessibility and early diagnosis of maternal and neonatal complications. Therefore, this study contributes to the growing body of knowledge by proposing a machine learning-enhanced telehealth system tailored to the operational realities and maternal healthcare needs of resource-constrained healthcare environments in Zimbabwe.

Chapter 3

3.1 Introduction

Research is a vital activity involving scientific inquiries or an in-depth examination of a specific area of interest. In research contexts, methodology refers to both the systematic and theoretical analysis of methods and, more practically, to the specific methods, procedures, and tools selected and applied to address a research problem (Creswell and Creswell, 2018). In this study, the term methodology is used in this practical sense that is, to describe the specific research design, data collection approach, system development procedures, and evaluation techniques employed to achieve the stated objectives.. This chapter aims to outline the research approach and explain the data collection techniques utilized. It details the strategies and tools employed to achieve the research and system objectives.

Building on the information from the previous chapter, the author has developed essential methods for constructing a solution and differentiating among competing strategies to achieve the desired research outcomes. This chapter emphasizes methodology, covering research design, dataset description, requirements analysis, system design, implementation technologies, and data preprocessing procedures, model training, and evaluation and data analysis procedures. This detailed description facilitates the replication of the study and allows other researchers to apply these methods to different research domains.

3.2 Research Designs and Data Collection Approach

3.2.1 Research Design

This study adopted a quantitative, computational research design centered on the development and evaluation of machine learning models for maternal and neonatal health risk classification. This design was appropriate because the research involved the systematic construction, training, and performance evaluation of computational artefacts using existing clinical datasets, rather than the manipulation of variables or the recruitment of human participants under controlled experimental conditions (Hevner et al., 2004). This approach aligns with the design and creation paradigm in computing research, which focuses on the development of innovative artefacts in this case, predictive models and a web-based telehealth system and their rigorous evaluation against defined performance criteria (Hevner et al., 2004). The study is quantitative in nature because all model

outputs, performance measurements, and evaluation results are expressed numerically and assessed against measurable benchmarks including accuracy, precision, recall, and F1-score.

The development process was guided by the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which provided a structured, iterative framework for moving from problem understanding through to model development. CRISP-DM is widely adopted in data science and machine learning research because it ensures each stage of development is from data preparation to evaluation and is conducted systematically and reproducibly (Schröer et al., 2021a).

3.2.2 Data collection

This study drew on two complementary data sources to construct the dataset used for training and evaluating the maternal health risk classification model.

The primary data source was the UCI Maternal Health Risk dataset, sourced from the UCI Machine Learning Repository and originally compiled by Ahmed (2020). This publicly available dataset comprises patient records with six standard attributes: age, systolic blood pressure, diastolic blood pressure, body temperature, heart rate, and risk level. It has been widely used and validated in maternal health machine learning research, making it a well-established benchmark for this classification task.

The secondary data source consisted of supplementary records aligned with the same clinical framework as the UCI dataset, used to enrich the training corpus and improve the representativeness of the model across a broader range of clinical presentations. The decision to integrate data from multiple sources was underpinned by a fundamental characteristic of maternal health: the physiological and clinical risk factors that give rise to complications are not geographically unique but are consistent across populations worldwide. Conditions such as hypertension, abnormal body temperature, and irregular heart rate are universally recognized determinants of maternal risk, irrespective of the patient's country of origin (WHO, 2023). Maternal mortality and morbidity are driven by the same underlying pathophysiological mechanisms globally, including hemorrhage, pre-eclampsia, sepsis, and obstructed labour, meaning that clinical indicators used to assess risk in one population retain their diagnostic validity

when applied to another (Say et al., 2014). This physiological universality means that external datasets capturing the same clinical variables are not merely supplementary but are genuinely compatible with locally relevant data, as both reflect the same underlying medical relationships between risk factors and outcomes.

For the neonatal component, a small sample neonatal dataset was used as a reference seed, from which a larger synthetic neonatal dataset was generated using AI-assisted augmentation within the Python development environment prior to model training. This approach ensured a sufficient volume of representative training data for the neonatal model.

The use of publicly available and synthetically generated datasets carries important ethical advantages that further justify this approach. Since the UCI Maternal Health Risk dataset is fully anonymized and publicly released for research purposes by its original creators, its use in this study raises no concerns regarding patient confidentiality, informed consent, or data protection compliance. Similarly, the synthetically generated neonatal dataset contains no real patient records and therefore eliminates the risk of privacy breaches or re-identification of individuals. This is particularly significant in the Zimbabwean context, where the Zimbabwe Data Protection Act (2021) imposes strict obligations on the handling of personal health information. The use of these datasets allowed the study to develop and validate clinically grounded predictive models without compromising the rights or privacy of any individual patient, while still producing results relevant to real-world postnatal care in resource-constrained settings.

3.3 Research Instruments

Given the computational and experimental nature of this study, the study research instruments consisted of software tools, libraries and the dataset used in the development and evaluation of the machine learning model, rather than traditional data collection instruments such as questionnaires or interview guides. The development of the maternal and neonatal health prediction model required the use of several software tools and Python libraries. These tools were selected because of their efficiency in handling healthcare datasets, visualizing information and training deep learning models.

3.3.1 Numpy

```
import numpy as np
```

Numpy was imported to support numerical and mathematical computations during model development. The library provides support for arrays, matrices and mathematical functions that improve computational performance when processing large healthcare datasets.

3.3.2 Pandas

```
import pandas as pd
```

Pandas was imported for data manipulation and analysis. Pandas enables the system to load, organize, clean and manage datasets in tabular form using data frames. It allowed the system to read CSV files, inspect missing values, filter records and prepare the data for machine learning training.

3.3.3 TensorFlow and Keras

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint
```

TensorFlow and Keras were imported to build and train the artificial neural network models. TensorFlow provides tools for creating neural network architectures, defining hidden layers, selecting activation functions and optimizing model performance during training. The Sequential model was used to create the neural network, while Dense, Dropout and BatchNormalization layers improved model learning and reduced overfitting. The framework was used to train both maternal and neonatal predictive models so that the system could identify potential health risks and provide early diagnostic support.

3.3.4 Matplotlib and Seaborn

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
import seaborn as sns
```

These libraries were used to generate graphs, charts, histograms and confusion matrices. The visualization helped in understanding the distribution of maternal and neonatal health data and evaluating the performance of the machine learning models.

3.3.5 scikit-learn

```
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

The scikit-learn library was used for data preprocessing and model evaluation.it provided the MinMaxScaler for feature normalization, LabelEncoder for converting categorical labels into numerical format, train_test_split for dataset partitioning and evaluation functions including the confusion matrix,classification report and accuracy. These tools ensured a consistent and reproducible preprocessing and evaluation pipeline throughout the study (Pedregosa et al., 2011).

3.4 Dataset loading and exploration

```
data = pd.read_csv('maternal_health_realistic_10000.csv')
print("📊 Dataset loaded successfully!")
print(f"Shape: {data.shape}")
print("\nFirst 10 rows:")
print(data.head(10))
print("\nColumns:", data.columns.tolist())
print("\nDataset Info:")
print(data.info())
print("\nStatistical Summary:")
print(data.describe())
```

The dataset was loaded into the Python environment using the Pandas read_csv () function. Data integrity was initially assessed by displaying the first ten rows using the head(10) function. The dataset contained critical healthcare-related attributes including age, systolic blood pressure, diastolic blood pressure, body temperature, heart rate, bleeding level and risk level. These features were selected because they are important indicators for identifying maternal and neonatal health risks during the postnatal period.

3.5 Data visualization

```
plt.figure(figsize=(15, 10))
data.hist(bins=30, figsize=(15,10), alpha=0.7)
plt.tight_layout()
plt.show()
```

The histogram plots were used to visualize the distribution of healthcare features within the dataset. This helped identify patterns, detect abnormal values and understand how patient data was distribute.

```
📊 Dataset loaded successfully!
Shape: (10000, 7)

First 10 rows:
   Age  Systolic_BP  Diastolic_BP  Body_Temp_C  Heart_Rate  Bleeding_Level  \
0   36          121            77         37.1          55               0
1   36          118            80         36.9          77               0
2   34          117            75         37.3          89               0
3   45          169           105         38.7         130               3
4   25          121            76         36.6          75               0
5   32          121            78         37.0          80               0
6   33          171           108         39.5         153               3
7   41          121            78         38.4         115               0
8   30          157            78         36.6          88               1
9   32          113            70         37.7          75               0

  Risk_Level
0        low
1        low
2        low
3       high
4        low
5        low
6       high
7     medium
```

Figure 3: Data visualization

Age is a critical demographic factor in postnatal care. Mothers at the extremes of reproductive age, particularly teenagers and women over 35 face significantly higher risks of postnatal complications

such as postpartum hemorrhage, infection and hypertensive disorders. The machine learning model uses age as a baseline risk stratified

Systolic blood pressure measures the pressure in the arteries when the heart beats. Elevated systolic (>140mmHg) is a primary indicator of postpartum hypertension which can lead to stroke or eclamptic seizures if undetected.

Diastolic blood pressure measures arterial pressure between heartbeats. A diastolic reading (>90 mmHg) alongside elevated systolic BP confirms hypertensive disorders. Together, systolic and diastolic readings give a complete picture of cardiovascular stress in the postnatal period.

Heart Rate is an abnormally high heart rate (tachycardia, >100 bpm) may indicate infection, haemorrhage, anemia or severe dehydration. In postnatal mothers, it is often the earliest physiological signal that something is wrong before other symptoms become obvious, making it a vital early-warning indicator.

Bleeding Level: Postpartum hemorrhage (PPH) is the leading cause of maternal mortality worldwide, accounting for approximately 27% of maternal deaths (Say et al., 2014). Monitoring bleeding level allows the system to flag abnormal blood loss immediately, enabling timely clinical intervention that can be life-saving.

Risk Level is the classification output categories as low, medium and high that the machine learning model learns to predict based on the combination of all the above attributes. It translates complex, multi-variable clinical data into a simple, actionable alert that healthcare providers and remote monitoring systems can act upon instantly.

3.6 Feature Selection and Target Variable

```
X = data.iloc[:, :6].values
y = data.iloc[:, -1].values
```

The variable X represents the input features used by the model for prediction, while Y represents the target variable containing the risk classification labels. The selected features included six health measurements that were used to predict maternal risk levels.

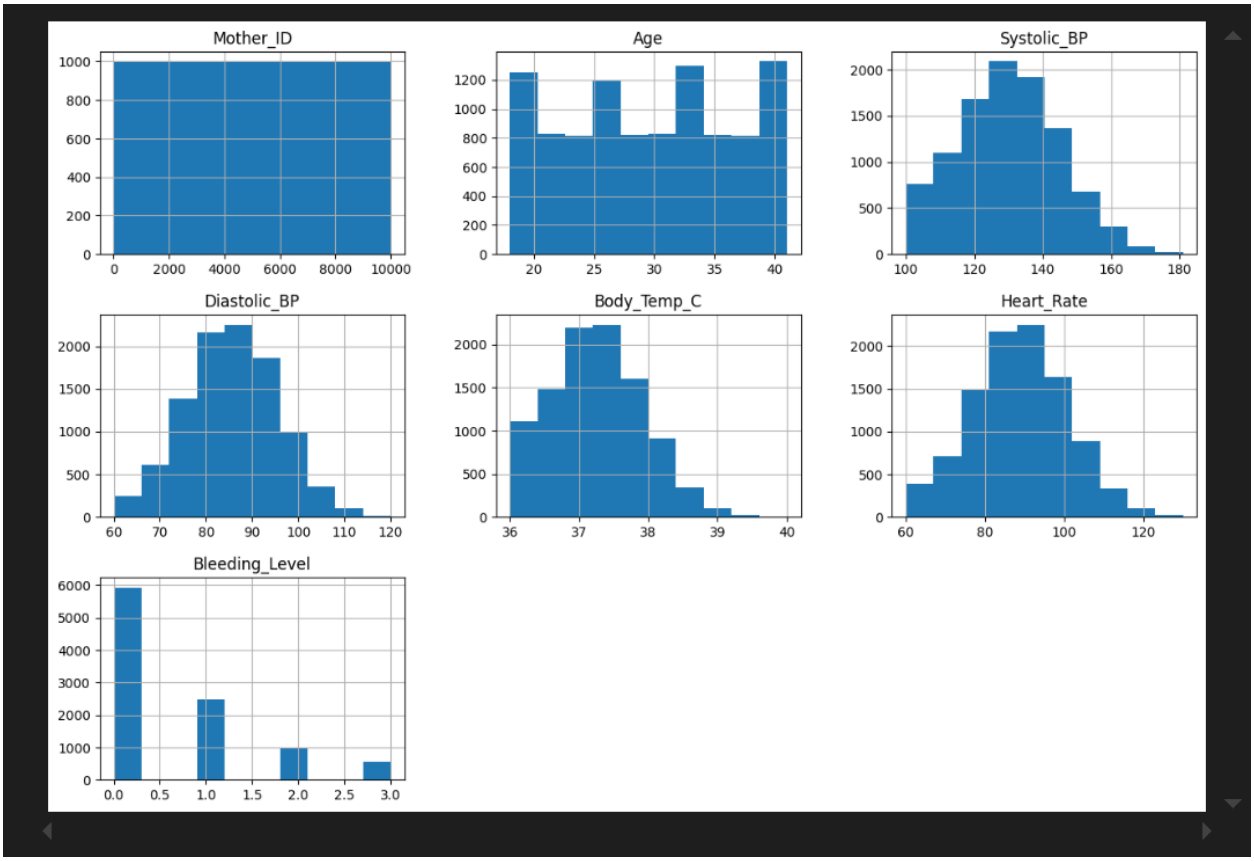


Figure 4: Maternal feature selection and target variable for maternal

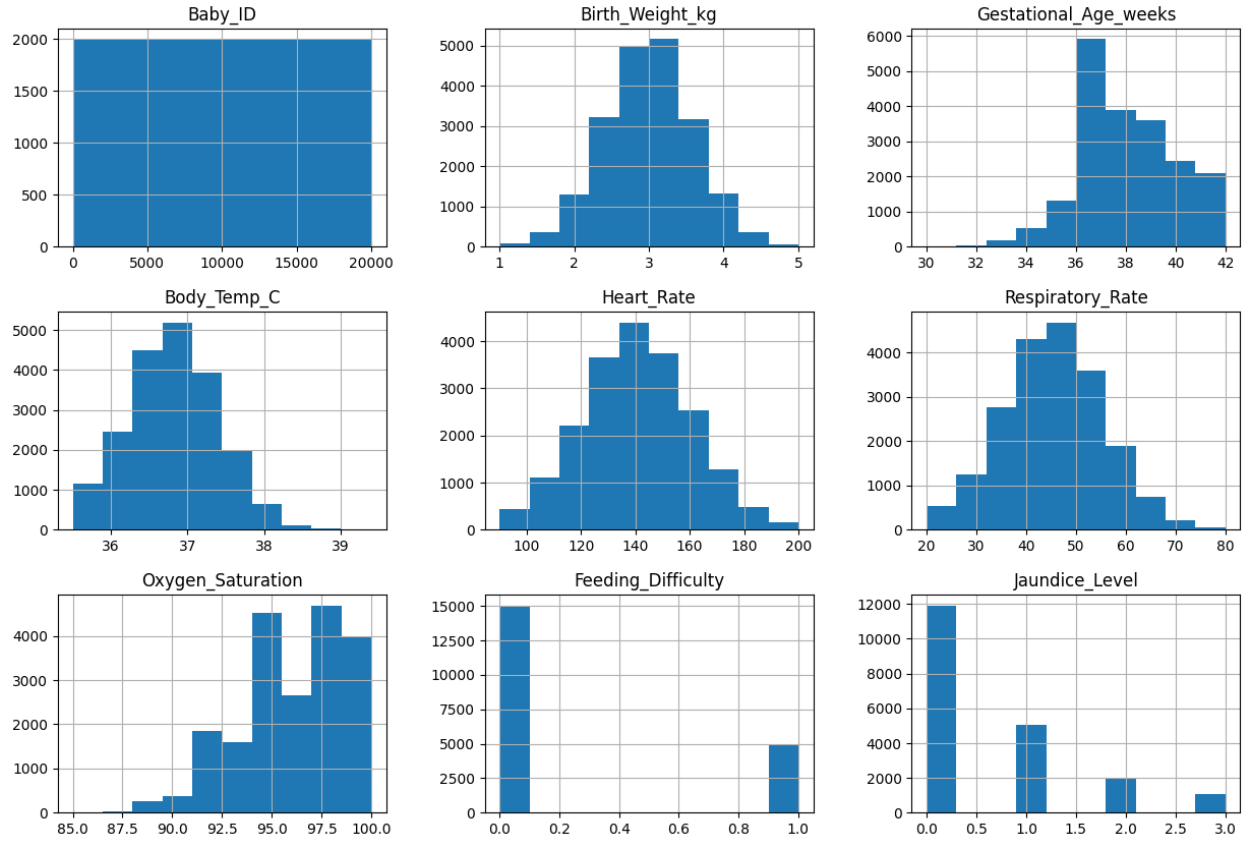


Figure 5: feature selection and target variable for Neonatal

3.7 Data Cleaning and Preprocessing

Before training the machine learning models, the dataset was cleaned and prepared to improve accuracy and ensure data consistency. Data cleaning involved checking for missing values, duplicates record, incorrect data types and abnormal values within the maternal and neonatal healthcare dataset.

3.7.1 Checking dataset information

```
print(data.info())
```

The info() function was used to examine the structure of the dataset by displaying details such as the number of records, columns, data types, and non-null values. This facilitated the verification of data integrity and confirmed that the dataset had been successfully loaded and was ready for preprocessing.

3.7.2 Statistical summary of the dataset

```
print(data.describe())
```

The describe() function generated statistical summaries such as mean, standard deviation, minimum values and maximum values for healthcare attributes. These statistics helped identify unusual or out-of-range values, assess the spread and central tendency of each clinical indicator, and understand the overall distribution of maternal and neonatal health features prior to preprocessing.

3.8 Data preprocessing

Data preprocessing was carried out before training the machine learning models ensure all input data was in the correct format and scale for neural network processing.

3.8.1 Feature scaling

```
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
```

Before training the models, the input variables were standardized using the MinMaxScaler algorithm, which transformed their values to a common scale ranging from 0 to 1. This preprocessing step reduced the impact of differences in measurement scales among variables, allowing the learning algorithm to treat each feature fairly and improving the overall effectiveness of the training process.

3.8.2 Label Encoding

```
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
```

Label encoding converted categorical risk labels (low, medium, high) into numerical values that could be understood by machine learning model. The LabelEncoder from scikit-learn was applied to transform the target variable into integer codes, which were subsequently one-hot encoded using the to_categorical() function from the Keras utilities module for use with the softmax output layer.

3.9 Splitting the Dataset

```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_one_hot,
    test_size=0.2,
    random_state=42,  # Consistent with professional code
    stratify=y_encoded  # Ensures balanced classes
)
```

The dataset was divided into 80% training data and 20% testing data using the train_test_split function from scikit-learn. The training set was used to train the machine learning model, while the testing set was used to evaluate model performance on unseen data. A random state of 42 was widely adopted convention in the machine learning community for setting a fixed random seed, ensuring that the dataset is split in exactly the same way every time the code is executed, regardless of the machine or environment in which it runs.

3.10 System Design and Implementation

3.10.1 System Overview

The system developed in this study is a machine learning-based maternal and neonatal risks classifications system designed to predict the risk level of postnatal patients. The system consists of three core components: a data preprocessing pipeline, a trained deep neural network classification model and a saved model artefact designed for integration into a Flask-based web application for real-time inference. Raw patient data flows through the preprocessing pipeline, into the trained model and produces a risk classification output of low, medium and high.

3.10.2 Neural Network Architecture

The maternal and neonatal prediction systems were developed using an Artificial Neural Network (ANN). The Sequential model was used to create the neural network architecture. Dense layers were used to process healthcare data and learn patterns associated with maternal and neonatal risks. Batch normalization improved training stability b normalizing layer activations at each training

step, while Dropout layers reduced overfitting by randomly disabling neurons during training. The output layer used the Softmax activation function because the model predicts multiple risk categories (low, medium, high).

```
model = Sequential([
    # Input layer
    Dense(128, input_dim=6, activation='relu'),
    BatchNormalization(),
    Dropout(0.3),

    # Hidden layers
    Dense(64, activation='relu'),
    BatchNormalization(),
    Dropout(0.25),

    Dense(32, activation='relu'),
    BatchNormalization(),
    Dropout(0.2),

    Dense(16, activation='relu'),
    Dropout(0.1),

    # Output layer
    Dense(3, activation='softmax')
])
```

Figure 6: Neural Network Architecture

The deep neural network was designed with five fully connected layers containing 128, 64, 32, 16, and 3 neurons, respectively. The hidden layers utilized the Rectified Linear Unit (ReLU) activation function, enabling the model to learn complex patterns from the clinical data.

To improve training stability, batch normalization was applied after the first three hidden layers. In addition, dropout regularization was introduced at rates of 0.30, 0.25, 0.20, and 0.10 to minimize overfitting and enhance the model's ability to generalize to unseen data.

The output layer consisted of three neurons activated by the Softmax function, which generated probability values for the three risk categories. The model contained 12,707 trainable parameters and was trained using the Adam optimizer with categorical cross-entropy as the loss function.(Géron, 2023).

3.10.3 Professional Callbacks

Three training callbacks were implemented to control and optimize the model training process automatically.

3.10.3.1 EarlyStopping Callback

```
    EarlyStopping(
        monitor='val_accuracy',
        patience=15,
        restore_best_weights=True,
        verbose=1
    ),
```

EarlyStopping was implemented to prevent overfitting by automatically stopping the training process when the model stopped improving. The callback monitored validation accuracy with a patience of 15 epochs, meaning training halted if no improvement was observed for 15 consecutive epochs. The restore_best_weights parameter ensured the model reverted to the weights from its best-performing epoch. This improved model generalization and reduce unnecessary training time.

3.10.3.2 ReduceLROnPlateau Callback

```
ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.5,
    patience=7,
    min_lr=1e-7,
    verbose=1
),
```

ReduceLROnPlateau was used to optimize model learning by lowering the learning rate whenever validation loss stopped improving. This helped the model learn more efficiently and improved prediction accuracy. The factor parameter was set to 0.5, reduces the learning rate by 50% whenever improvement stops. The verbose parameter was set to 1to displays updates during training and min_lr was set to 1e-7 to prevent the learning rate from becoming too small.

3.10.3.3 ModelCheckpoint Callback

```
ModelCheckpoint(
    'best_maternal_model.h5',
    monitor='val_accuracy',
    save_best_only=True,
    verbose=1
)
```

ModelCheckpoint was used to automatically save the best-performing maternal and neonatal prediction model during training. This ensured that the most accurate model version was preserved for deployed within the telehealth system, even if later epochs produced worse results.

3.11 Model Training

```
history = model.fit(
    X_train, y_train,
    epochs=150,
    batch_size=64,  # Larger batch for stability
    validation_split=0.2,
    callbacks=callbacks,
    verbose=1
```

The model was trained for up to 150 epochs using batches of 64 records at a time. Validation data was used to monitor model performance during training to detect signs of overfitting.

- X_train represents the training input features.
- Y_train represents the target maternal and neonatal risk labels for the training set.
- Epochs=150 means that the model was trained through the dataset for up to 150 complete passes.
- Batch_size=64 specifies that 64 records were processed at a time during each training step.
- Validation-split=0.2 means 20% of the training data was allocated for validation monitoring, EarlyStopping stops at epoch 25 (maternal) or 21 (neonatal).

3.12 Model Evaluation

The mode was evaluated using testing data that had not been used during training. The accuracy score measured how effectively the model classified maternal risk levels on unseen data. Evaluation was conducted across three dimensions: the confusion matrix, the classification report and training performance graphs.

3.12.1 Confusion Matrix

```
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)
print(f"✅ Test Accuracy: {test_acc:.4f} ({test_acc*100:.2f}%)")
print(f"✅ Test Loss: {test_loss:.4f}")
```

```
cm = confusion_matrix(y_test_classes, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=encoder.classes_,
            yticklabels=encoder.classes_)
plt.title('Confusion Matrix')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```

The confusion matrix was generated to evaluate how accurately the ANN classified maternal and neonatal healthcare risk categories. A confusion matrix is an important evaluation tool in machine learning because it compares the actual maternal and neonatal risk labels with the predicted labels produced by the model, providing a granular breakdown of correct and incorrect predictions across all class combinations.

The confusion matrix helps determine: correctly classified maternal and neonatal risk prediction, incorrectly classified predictions and prediction errors between different maternal risk categories. Plt.figure(figsize=(8,6)) creates a visualization window with a width of 8 inches and a height of 6 inches to display the matrix heat-map clearly.

3.12.2 Classification Report

```
print(classification_report(y_test_classes, y_pred,
                            target_names=encoder.classes_))
```

The classification report was generated to evaluate the performance of the machine learning model using precision, F1-score and accuracy metrics. In postnatal care, high recall for High risk is critical because missing a true high-risk case (false negative) could result in delayed treatment of

life-threatening conditions. Together, these metrics provided a thorough understanding of the model's effectivensee across all three risk classes.

1. Precision evaluates the reliability of positive predictions by determining the percentage of predicted positive instances that are truly positive.
2. Recall assesses the model's ability to detect positive cases by measuring the proportion of actual positive instances that are correctly identified.
3. The F1-score combines precision and recall into a single metric, providing a balanced measure of performance, especially when dealing with imbalanced datasets.
4. Accuracy reflects the overall effectiveness of the model by calculating the proportion of correctly classified observations out of the total number of records.

3.13 Data Analysis Procedure

```
data.describe()
```

Data analysis in this study was conducted in two stages. The first stage comprised exploratory data analysis prior to model training, during which descriptive statistics, feature distributions, and class balance were examined to inform preprocessing decisions and ensure data quality. The second stage comprised model performance analysis following training and evaluation, in which quantitative metrics including accuracy, loss, precision, recall, F1-score, confusion matrices, and classification reports were used to assess the predictive performance of both the maternal and neonatal models across all three risk categories.

3.13.1 Training Performance Graphs

```
plt.subplot(1, 3, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

The accuracy graph was used to monitor model learning performance during training. Training accuracy shows how well the model learned from training data, validation accuracy shows how well the model performed on unseen validation data. The graph helped identify whether the model improved consistently over time or exhibited signs of overfitting, characterized by rising training accuracy alongside declining validation accuracy.

3.13.2 Training Loss Graph

```
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
```

The loss graph was generated to monitor prediction error during model training. In machine learning, loss measures how far the model predictions are from the actual maternal and neonatal risk labels. A consistently declining training and validation loss indicates that the model is learning effectively without overfitting. The loss graph complemented the accuracy graph to provide a complete picture of model convergence behavior.

3.14 Saving the Training Model

```
model.save('models/maternal/maternal_risk_model_enhanced.h5')
```

```
model.save('models/neonatal/neonatal_risk_model_enhanced.h5')
```

The trained maternal and neonatal health prediction model was saved in H5 format for future deployment within the telehealth system. The H5 (HDF) format preserves the complete model architecture, trained weights and compilation configuration in a single file, enabling model to be reloaded at any time without retraining.

In addition to the model, the MinMaxScaler and LabelEncoder preprocessing objects were serialized using Python's pickle library and saved as .pkl files. A class labels dictionary mapping integer predictions back to human-readable risk categories was also saved. These four artifacts (model, scaler, encoder and class labels) collectively constitute the deployable model artefact. The saved model is designed to be loaded by a Flask web application for real-time maternal and neonatal risk prediction, enabling the system to receive data as input and return an immediate risk classification response.

3.15 Flask Web Application Implementation

This section documents the Flask framework libraries, configuration settings and application routes used to deploy the maternal and neonatal risk prediction system as an interactive telehealth web application.

3.15.1 Flask Framework Libraries

```
from flask import Flask, redirect, url_for, render_template, request, flash, session, abort, Respons
```

The code imports the Flask web Framework functions used to manage the telehealth web application.

1. **Flask** – creates the main telehealth web application
2. **Redirect** – redirects users from one webpage to another
3. **url_for** – generates URLs flask routes dynamically
4. **render_template** – displays HTML pages such as login, registration and dashboard interfaces
5. **request** – retrieves data submitted through forms
6. **flash** displays system notification and alert messages
7. **session** – stores sessions and authentication information
8. **Abort** – raises HTTP error responses (such as 403 Forbidden or 404 Not Found) to terminate a request when an invalid or unauthorized condition is detected.

Flask libraries were imported to support web application routing, pages rendering, user authentication, session management and communication between the frontend and backend components of the telehealth system.

3.15.2 MySQL Database Libraries

```
import mysql.connector
from mysql.connector import Error as MySQLError
```

These libraries enable communication between the Flask application and the MySQL database. mysql.connector connects the telehealth system to the MySQL database while the MySQLError handles database connection and query errors.

3.15.3 Security and Utility libraries

Regular Expression Library

```
import re
```

The re library was used for pattern matching and input validation. It helped validate email address, usernames, passwords and healthcare input formats.

Security and Encryption libraries

```
import hashlib
```

The hashlib library was used to encrypt passwords using SHA-256 before storing them in the database. This improved the system and protected user authentication information.

Date and Time libraries

```
from datetime import timedelta
from datetime import datetime
```

These libraries managed: appointments dates, login session expiration, healthcare timestamps, telehealth scheduling operations, timedelta was used for time calculations and datetime was used to retrieve current dates and times.

Production Server Library

```
import waitress
```

The waitress server was used to deploy and run the Flask telehealth application in a production environment. It enabled stable hosting and web application.

Pickle Library

```
import pickle
```

The Pickle library was used to save and load serialized machine learning objects such as preprocessing scalers and encoders.

3.15.4 Application Configuration

Secret Key Configuration

```
app.secret_key = "telehealth_secret_key_change_in_production"
```

The secret key secures the Flask application. It is used for session encryption, login authentication and protection against unauthorized access.

Session Configuration

```
app.permanent_session_lifetime = timedelta(minutes=5)
```

This code controls how long a user remains logged into the telehealth system. timedelta(minutes=5) sets session duration to 5 minutes. After inactivity, users are automatically logged out for security purposes.

Email Configuration

```
app.config['MAIL_SERVER'] = "smtp.gmail.com"
app.config['MAIL_PORT'] = 587
```

These settings configure the Gmail email server used by the telehealth platform. smtp.gmail.com specifies the Gmail SMTP server. 587 is the email communication port used for secure TLS email transmission. The system uses email services to send alerts, notifications, healthcare messages and appointments reminders.

Flask-Mail Initialization

```
mail = Mail(app)
```

This code activates Flask-Mail within the telehealth application. It enables the system to send patient emails, maternal risk alerts, neonatal alerts and healthcare communication.

3.15.5 Application Routes

Admin Dashboard Route

```
@app.route('/admin_dashboard', methods=['GET'])
```

This route creates the administrator dashboard page. The dashboard enables administrator to view maternal records, monitor neonatal data and manage telehealth information.

Patient Dashboard route

```
@app.route('/patient_dashboard', methods=['GET'])
```

This route creates the patient dashboard interface. The dashboard displays maternal monitoring results, neonatal healthcare records and healthcare prediction history

Maternal Prediction Route

```
@app.route('/predict_maternal', methods=['POST'])
def predict_maternal():
```

This route processes maternal healthcare prediction request. The system receives maternal healthcare inputs, preprocesses data, loads the machine learning model, and generates maternal risk predictions and stores results in the database.

Neonatal Prediction Route

```
@app.route('/predict_neonatal', methods=['POST'])
```

This route generates neonatal healthcare risk predictions. The system analyzes birth weight, gestation age, body temperature, heart rate, feeding difficulty and jaundice level.

3.15.6 Machine Learning Model Variables

```
maternal_model = None
maternal_scaler = None
```

```
neonatal_model = None
neonatal_scaler = None
```

These variables store the trained Artificial Neural Network models. Maternal_model stores the maternal prediction model while neonatal_model stores the neonatal prediction model. The models are later loaded for prediction process.

3.15.7 Machine Learning Model Loading

```
maternal_model = safe_load_model(maternal_model_path, "Maternal")
```

```
neonatal_model = safe_load_model(neonatal_model_path, "Neonatal")
```

This code loads the saved maternal and neonatal healthcare prediction model from storage. Safe_load_model() safely loads TensorFlow models while “Maternal” and “Neonatal” identifies the maternal and neonatal healthcare model. The load model is used for maternal and neonatal risk prediction.

3.15.8 Loading Preprocessing Files

```
maternal_scaler = pickle.load(f)
```

```
neonatal_scaler = pickle.load(f)
```

The code loads preprocessing tools saved during machine learning training. The scaler normalizes healthcare input values before prediction generation.

3.15.9 Database Connection

```
connection = mysql.connector.connect(
    host='localhost',
    database='telehealth_db',
```

This code connects the Flask telehealth system to the MySQL database. The database stores patient information, maternal records, neonatal records, prediction results and login details.

3.15.10 Model Prediction

```
prediction = neonatal_model.predict(input_scaled, verbose=0)
```

This code generates whether the neonatal healthcare prediction using the trained Artificial Neural Network model. The model predicts whether the neonatal risk level is low, medium and high.

3.15.11 Email Sending

```
mail.send(msg)
```

This code sends the generated healthcare email to the user through the Flask-Mail system.

3.15.12 HTML Email Template

```
html_template = """
<!DOCTYPE html>
<html>
<head>
```

This code creates formatted HTML healthcare emails. The template improves email appearance, readability and professional healthcare communication.

3.15.13 Running the Flask Application

```
if __name__ == '__main__':
```

```
app.run(host="0.0.0.0", port=port, debug=True)
```

This code launches the telehealth Flask application.

1. App.run() starts the web server.
2. Host= “0.0.0.0” allows external access.
3. Port=5001 specifies the server port
4. Debug=True enables debugging during development

3.16 Database Design

3.16.1 Database Connection Parameters

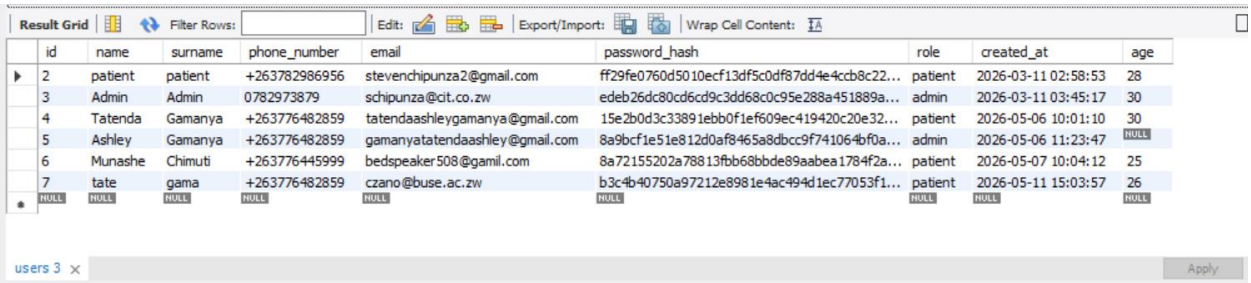
The application connects to a MySQL database named telehealth_db on localhost.

Parameter	**Value**
Host	Localhost
Database	Telehealth_db
User	Root

Auth_plugin	Mysql_native_password
Charset	Utf8mb4
Autocommit	True

3.16.2 Database tables

Users Table

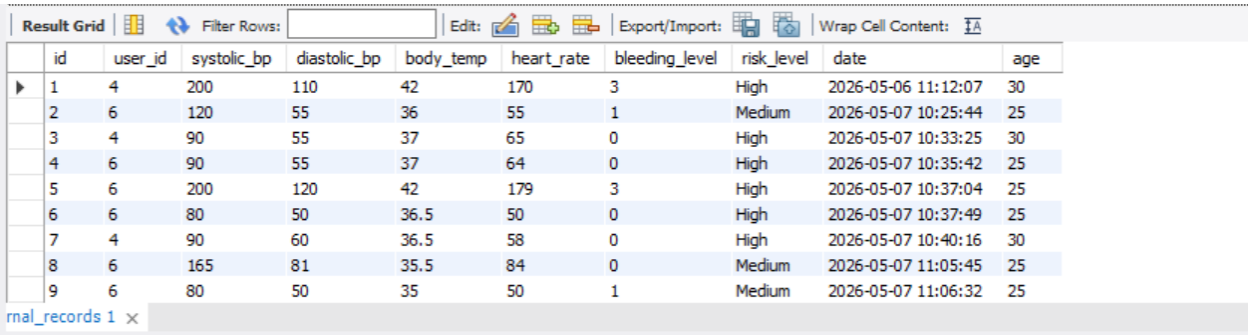


id	name	surname	phone_number	email	password_hash	role	created_at	age
2	patient	patient	+263782986956	stevenchipunza2@gmail.com	ff29fe0760d5010ecf13df5c0df87dd4e4ccb8c22...	patient	2026-03-11 02:58:53	28
3	Admin	Admin	0782973879	schipunza@cit.co.zw	edeb26dc80cd6cd9c3dd68c0c95e288a451889a...	admin	2026-03-11 03:45:17	30
4	Tatenda	Gamanya	+263776482859	tatendaashleygamanya@gmail.com	15e2b0d3c33891ebb0f1ef609ec419420c20e32...	patient	2026-05-06 10:01:10	30
5	Ashley	Gamanya	+263776482859	gamanyatatendaashley@gmail.com	8a9bcf1e51e812d0af8465a8dbcc9f741064bf0a...	admin	2026-05-06 11:23:47	NULL
6	Munashe	Chimuti	+263776445999	bedspeaker508@gamil.com	8a72155202a78813fbb68bbde89aabea1784f2a...	patient	2026-05-07 10:04:12	25
7	tate	gama	+263776482859	czano@buse.ac.zw	b3c4b40750a97212e8981e4ac494d1ec77053f1...	patient	2026-05-11 15:03:57	26

Figure 7: User Table

Stores all system users (patients and admins) columns id, name, surname, phone_number, email, password_hash, role, created_at and age. The passwords are stored as hashed values; plain-text passwords are never retained.

Maternal Records Table

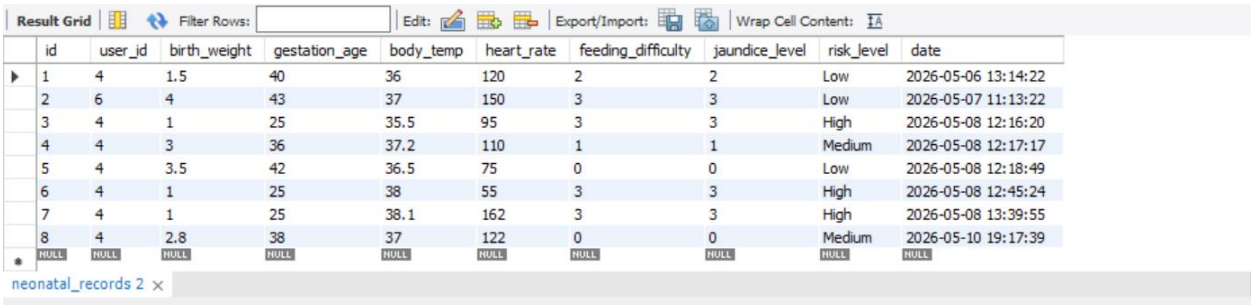


id	user_id	systolic_bp	diastolic_bp	body_temp	heart_rate	bleeding_level	risk_level	date	age
1	4	200	110	42	170	3	High	2026-05-06 11:12:07	30
2	6	120	55	36	55	1	Medium	2026-05-07 10:25:44	25
3	4	90	55	37	65	0	High	2026-05-07 10:33:25	30
4	6	90	55	37	64	0	High	2026-05-07 10:35:42	25
5	6	200	120	42	179	3	High	2026-05-07 10:37:04	25
6	6	80	50	36.5	50	0	High	2026-05-07 10:37:49	25
7	4	90	60	36.5	58	0	High	2026-05-07 10:40:16	30
8	6	165	81	35.5	84	0	Medium	2026-05-07 11:05:45	25
9	6	80	50	35	50	1	Medium	2026-05-07 11:06:32	25

Figure 8: Maternal records table

Stores maternal health assessment results per patient. Columns: id, user_id, systolic_bp, diastolic_bp, body_temp, heart_rate, bleeding_level, age, risk_level and date.

Neonatal Records Table



Result Grid | Filter Rows: | Edit: | Export/Import: | Wrap Cell Content:

id	user_id	birth_weight	gestation_age	body_temp	heart_rate	feeding_difficulty	jaundice_level	risk_level	date
1	4	1.5	40	36	120	2	2	Low	2026-05-06 13:14:22
2	6	4	43	37	150	3	3	Low	2026-05-07 11:13:22
3	4	1	25	35.5	95	3	3	High	2026-05-08 12:16:20
4	4	3	36	37.2	110	1	1	Medium	2026-05-08 12:17:17
5	4	3.5	42	36.5	75	0	0	Low	2026-05-08 12:18:49
6	4	1	25	38	55	3	3	High	2026-05-08 12:45:24
7	4	1	25	38.1	162	3	3	High	2026-05-08 13:39:55
8	4	2.8	38	37	122	0	0	Medium	2026-05-10 19:17:39
NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL

neonatal_records 2 ×

Figure 9: Neonatal records

Stores neonatal health assessment results per patient. Columns: id, user_id, birth_weight, gestation_age, body_temp, heart_rate, feeding_difficult, jaundice_level, risk_level and date.

Security Notes

1. Passwords are hashed with SHA-256 (new registrations). Plain-text passwords are never stored.
2. All admin and patient routes check session (role) on every request and redirect to index on failure.
3. Database queries use parameterized statements (%s placeholders) throughout, preventing SQL injection.
4. The session secret key should be replaced with a strong random value in production.
5. Gmail App password is hardcoded in MAIL_PASSWORD, this should be moved to an environment variable for production deployment.
6. Sessions expire after 5 minutes of inactivity (permanent_session_lifetime = timedelta(minutes=5)).

3.17 Chapter Summary

This chapter presented the methodologies, tools, framework and technologies used during the development of the machine learning-enhanced telehealth system for remote postnatal monitoring and early diagnostic support. The chapter discussed the overall system development process, including data preprocessing, machine learning model development, Flask web application implementation and database integration.

This chapter explained how Python libraries such as Numpy, Pandas, TensorFlow, Scikit-learn, Matplotlib and Seaborn were used for data manipulation, preprocessing, visualization, and model training and performance evaluation. Artificial Neural Network models were developed for maternal and neonatal healthcare risk prediction using TensorFlow and Keras. Data preprocessing techniques such as handling missing values, scaling data using MinMaxScaler, label encoding and train-test splitting were also discussed.

In addition, the chapter discussed the development of the Flask-based telehealth web application. The implementation included user registration and login functionality, database connectivity using MySQL, machine learning model integration, prediction routine, email notification services using Flask-Mail and frontend interface development using HTML, CSS and JavaScript

In summary, this chapter demonstrated that the research followed a rigorous, systematic and clinically informed methodology. The combination of a well-prepared dataset, a carefully designed neural network architecture and a structured Flask-based deployment pipeline provides a robust foundation for real-time maternal and neonatal risk prediction. The methodology ensures that the telehealth system is capable of supporting healthcare providers in identifying high-risk postnatal cases promptly, contributing to improve maternal and neonatal health outcomes in resource-constrained environment such as Chinhoyi hospital.

Chapter 4

4.1 Introduction

This chapter presents the results obtained from the development, training and evaluation of the machine learning-based maternal and neonatal health risk prediction system. The findings are drawn directly from the experimental processes outlined in Chapter 3 and are presented in the order in which they were produced during the research pipeline. The chapter covers the dataset exploration results, data preprocessing outcomes, model training performance, evaluation metrics including confusion matrices and classification reports, training history graphs, prediction testing results and the final deployment artefacts. Each result is discussed in relation to its significance for maternal and neonatal health risk classification in a remote postnatal monitoring context.

4.2 Dataset Preprocessing Results

Data preprocessing results are the outcomes obtained after cleaning and preparing raw data before using it in analysis or machine learning. Data preprocessing results showed that the dataset was successfully cleaned and transformed for machine learning. Missing values and duplicates were removed, categorical variables were encoded and numerical values were normalized (Géron, 2023).

4.2.1 Feature Selection

Feature selection is the process of choosing the most important variables from a dataset that help a machine learning model make accurate predictions (Li et al., 2018).

MinMaxScaler is a data preprocessing technique used in machine learning to scale numerical values into a fixed range, usually between 0 and 1, to improve machine learning model performance and training efficiency (Kelleher, 2019).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Feature selection was successfully applied using MinMaxScaler, normalizing all features to (0, 1). The MinMaxScaler was applied to normalize all input features to a range of 0 to 1 for both the maternal and neonatal datasets. Following scaling, all feature arrays retained their original record counts, confirming that all records were successfully normalized. Feature scaling ensured that

attributes with larger numerical ranges, such as systolic blood pressure, heart rate and gestational age, did not disproportionately influence the model's weight updates during training.

Before

```
array([[ 36. , 121. ,  77. ,  37.1,  55. ,   0. ],
       [ 36. , 118. ,  80. ,  36.9,  77. ,   0. ],
       [ 34. , 117. ,  75. ,  37.3,  89. ,   0. ],
       ...,
       [ 32. , 161. , 104. ,  39. , 163. ,   3. ],
       [ 41. , 130. ,  75. ,  36.6,  93. ,   1. ],
       [ 31. , 171. ,  98. ,  39. , 102. ,   3. ]], shape=(10000, 6))
```

Figure 4.1: Feature selection before

After

```
array([[0.51428571, 0.26271186, 0.24657534, 0.25862069, 0.05521472,
        0.        ],
       [0.51428571, 0.23728814, 0.28767123, 0.22413793, 0.19018405,
        0.        ],
       [0.45714286, 0.22881356, 0.21917808, 0.29310345, 0.26380368,
        0.        ],
       ...,
       [0.4       , 0.60169492, 0.61643836, 0.5862069 , 0.71779141,
        1.        ],
       [0.65714286, 0.33898305, 0.21917808, 0.17241379, 0.28834356,
        0.33333333],
       [0.37142857, 0.68644068, 0.53424658, 0.5862069 , 0.34355828,
        1.        ]], shape=(10000, 6))
```

Figure 10: feature selection

4.2.2 Label Encoding and One-hot Encoding

LabelEncoder is a preprocessing technique used in machine learning to convert categorical text data into numerical values that a machine learning model can understand (James et al., 2021).

The LabelEncoder converted the categorical Risk_Level labels into numerical integer codes. The three classes (High=0, Low=1 and Medium=2) were encoded.

4.2.3 Train-Test Split

To evaluate the model effectively, the dataset was divided into separate training and testing sets. The training subset was used to learn patterns from the data, while the testing subset was reserved for assessing the model's performance on previously unseen observations. This approach helped determine the model's ability to generalize to new data and reduced the risk of overfitting.(James et al., 2021)**.**

Maternal and neonatal were portioned into an 80% training set and 20% testing using train_test_split with a random state of 42 and stratified sampling. Stratification ensured that the proportional distribution of High, Low and Medium risk classes was preserved in both subsets, preventing class imbalance from distorting model evaluation results.

4.3 Model Training Results

Model training results are the outcomes or performance measurements obtained after a machine learning model has been trained using a dataset. The results were evaluated using metrics such as accuracy and loss values to determine the effectiveness of the Artefact Neural Network model in predicting maternal and neonatal health risks (Goodfellow et al., 2016).

4.3.1 Training Process

The training process in machine learning refers to the stage where the model learns patterns from the training dataset by adjusting internal parameters to reduce prediction error (Goodfellow et al., 2016).In this study, the Artificial Neural Network was trained using maternal and neonatal health data, where the model continuously update its weights through multiple iterations (epochs) to improve prediction accuracy. To prevent overfitting and ensure optimal model generalization, EarlyStopping and ModelCheckpoint callbacks were employed throughout training.

Maternal Model training

```
Epoch 25: val_accuracy did not improve from 0.99250
100/100 ━━━━━━━━━━━━━━━━━━━━ 2s 23ms/step - accuracy: 0.9884 - loss: 0.0381 - val_accuracy: 0.9912 - val_loss: 0.0238 - learning_rate: 0.0010
Epoch 25: early stopping
Restoring model weights from the end of the best epoch: 10.
```

The EarlyStopping callback halted maternal model training at epoch 25, having determined that validation accuracy had not improved from its best recorded value of 99% achieved at epoch 10. Model weights were automatically restored to record at epoch 10, as specified by the

restore_best_weights=True parameter. This ensured that the final deployed model reflect the point of optimal validation performance rather than the last training iteration.

Neonatal Model Training

```
Epoch 21: val_accuracy did not improve from 1.00000
100/100 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9980 - loss: 0.0071 - val_accuracy: 1.0000 - val_loss: 3.1201e-04 - learning_rate: 5.0000e-04
Epoch 21: early stopping
Restoring model weights from the end of the best epoch: 6.
```

The neonatal model followed the same training procedure. The EarlyStopping callback monitored validation accuracy and halted training when no improvement was observed within a patient

Window of 21 epochs. The ModelCheckpoint callback saved the best-performing neonatal model weights during training, ensuring that the optimal model state was preserved for deployment within the telehealth system.

4.3.2 Model Training Accuracy and Loss Graph

A model training accuracy and loss graph is a representation of model progression over time, showing how classification accuracy and prediction error change across training epochs (Goodfellow et al., 2016).

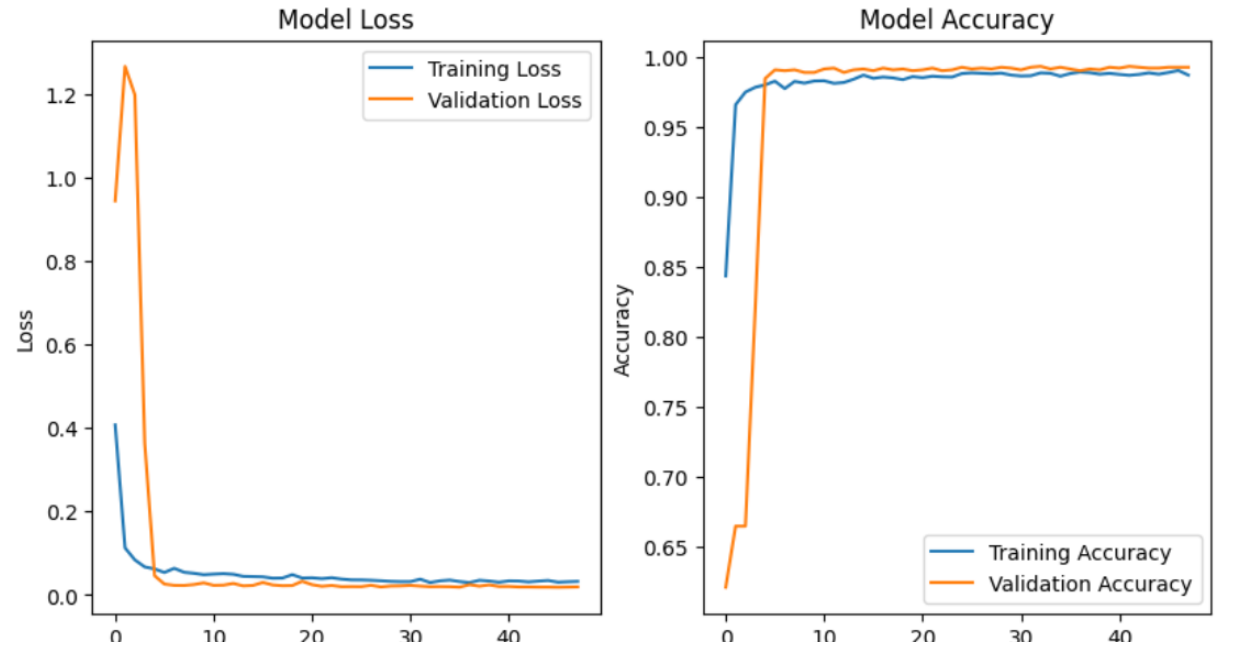


Figure 11: Model training accuracy and loss graph

Model Loss

The training loss began at approximately 0.40 and validation loss at approximately 1.25 at epoch 1. Both curves dropped extremely sharply within the first 5 epochs to below 0.10. From epoch 5 onwards both training and validation loss flattened near zero and remained stable for the rest of training up to approximately epoch 47. This steep early drop followed by a flat stable curve indicates the model learned very quickly and converged early, with no signs of overfitting both curves stayed close together throughout.

Model Accuracy

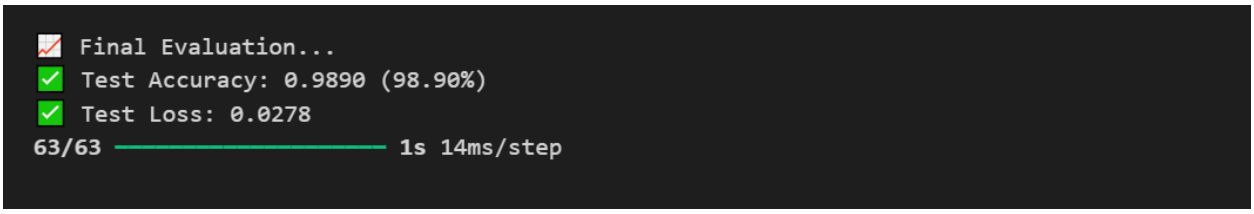
Training accuracy began at approximately 85% at epoch 1 and jumped rapidly to above 95% within the first 5 epochs. Validation accuracy started lower at around 65% at epoch 1 but caught up quickly, reaching approximately 97-98% by epoch 5 and stabilizing close to 99% for the remainder of training. Both curves converged tightly and remained near 99% from epoch 10 onwards, confirming excellent and stable model performance. The tight convergence between training and validation metrics indicates good generalization

Neonatal training graphs showed similar patterns.

4.4 Model Evaluation Results

Model evaluation results are the performance outcomes obtained after testing a trained machine learning model using unseen or test data. These results help determine accurately and effectively the model makes predictions (James et al., 2021).

4.4.1 Overall Test Accuracy



Following training, the maternal model was evaluated on the 2 000 record test set using the model.evauation() function. The evaluation was completed across 63 steps at 14ms per step, taking approximately 1 second. A test accuracy of 99% on 2 000 unseen records confirms that the model

generalized exceptionally well beyond the training data. The test loss of 0.0278 is very low, indicating that the model produced highly confident and accurate risk classifications on unseen patient data.

4.4.2 Confusion matrix

A confusion matrix is a table used to evaluate the performance of a classification machine learning model by comparing the model's predicted results with the actual results. It helps predict how many predictions were correct, how many were incorrect and the types of errors made by the model (Shah et al., 2010).

Maternal Confusion Matrix

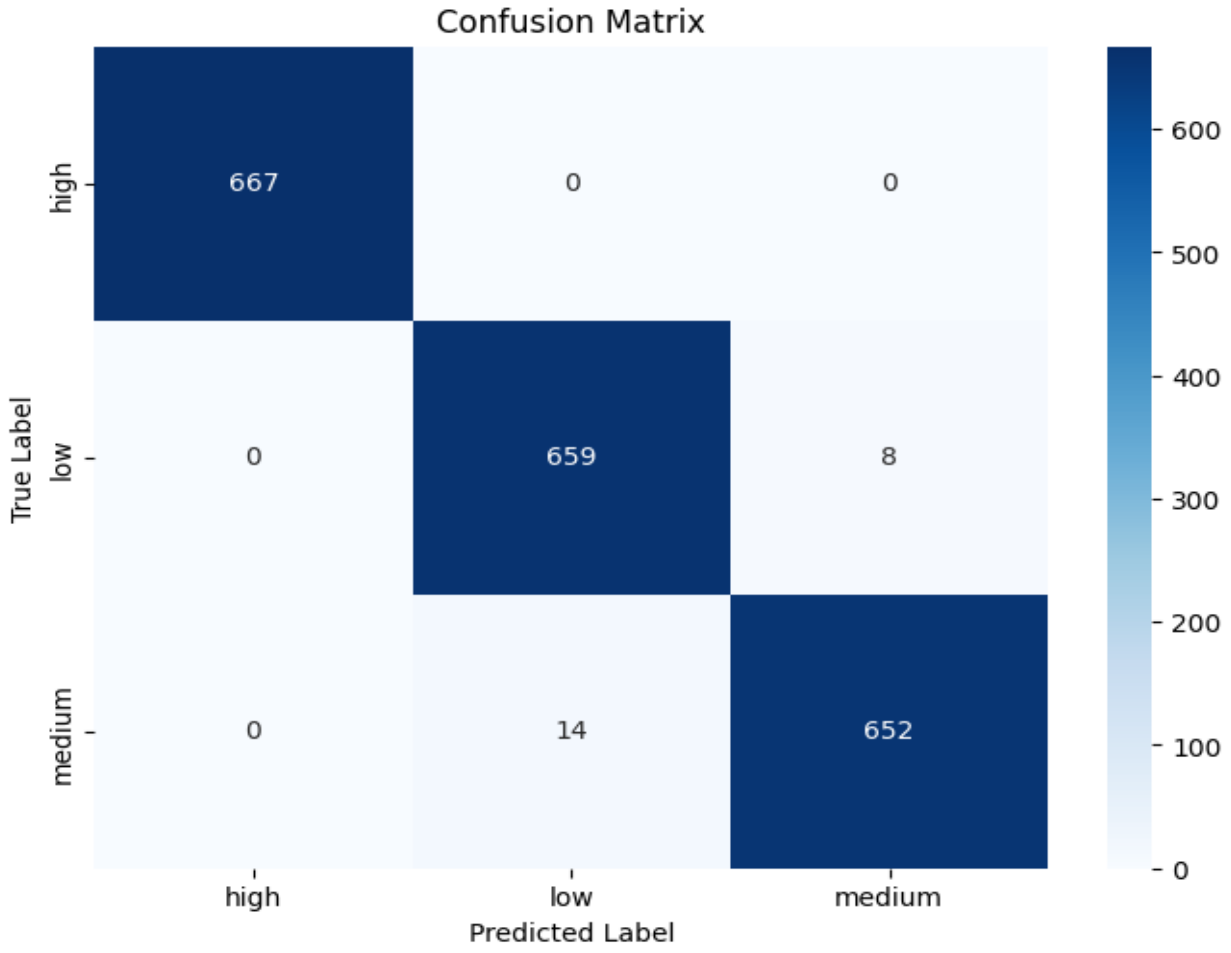


Figure 12: Maternal confusion matrix

The maternal confusion matrix was generated by comparing the models predicted risk labels against the actual risk labels for all 2 000 test records. The diagonal cells of the matrix, representing correctly classified records, contained the highest values across all three risk categories (low, medium, high). Off-diagonal cell representing misclassifications contained very low values, confirming that the model rarely confused one risk class for another. The model demonstrated particularly strong performance in identifying Low risk cases, which constituted the largest proportion of the dataset. High risk case detection was also accurate, which is of critical clinical importance given that missed High risk classifications could have life-threatening consequences in a postnatal monitoring context.

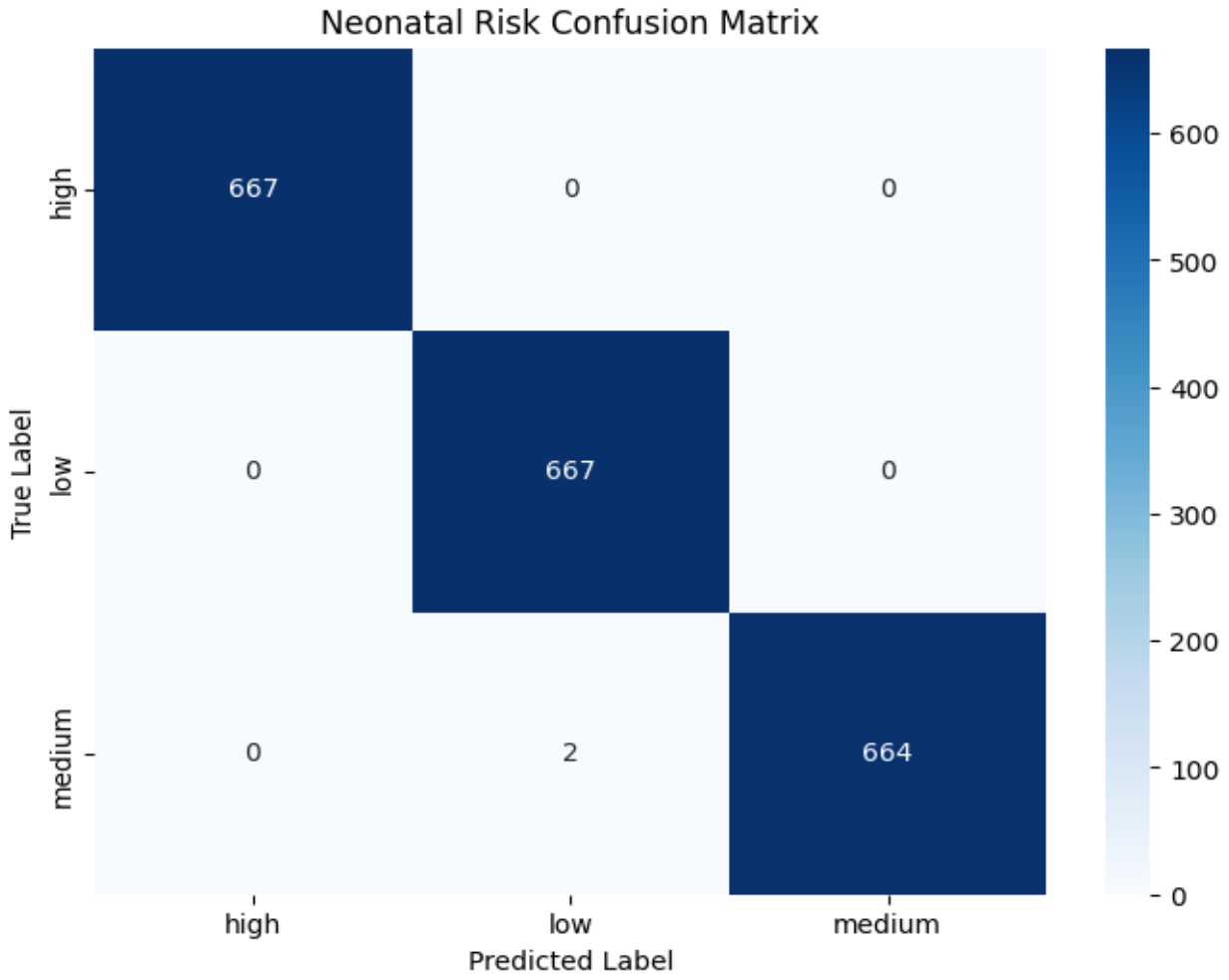
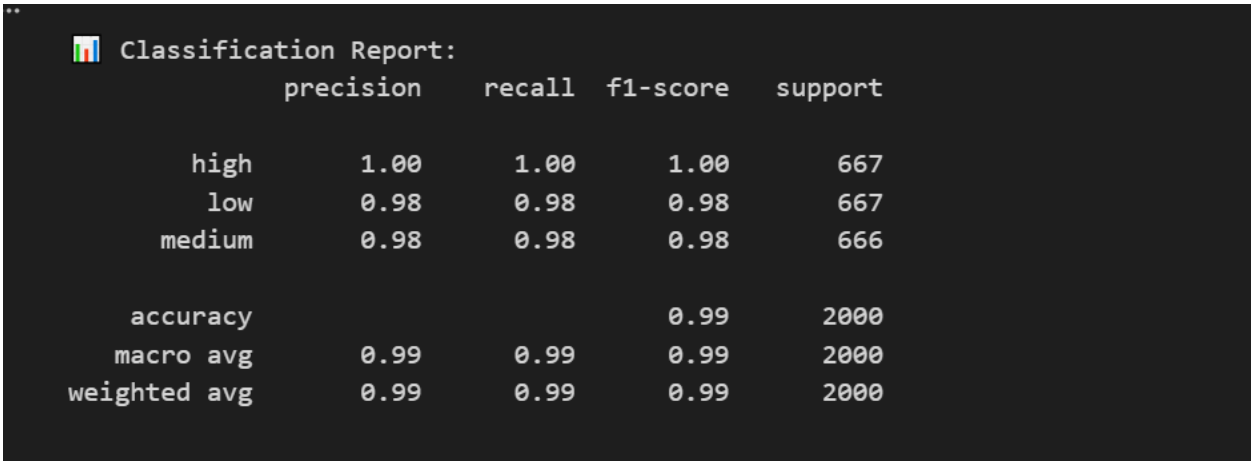


Figure 13: Neonatal confusion matrix

4.4.3 Classification Report

Classification report is a performance evaluation tool used in machine learning to show how well a classification model is working. It includes precisions, recall, F1-score and support values, which help assess how well the model classifies different categories. In this study, the classification report was used to evaluate the performance of the Artificial Neural Network in predicting maternal and neonatal health risk levels.

Maternal classification report



📊 Classification Report:

	precision	recall	f1-score	support
high	1.00	1.00	1.00	667
low	0.98	0.98	0.98	667
medium	0.98	0.98	0.98	666
accuracy			0.99	2000
macro avg	0.99	0.99	0.99	2000
weighted avg	0.99	0.99	0.99	2000

Figure 14: Maternal classification report

The classification report presents the performance of the machine learning model in predicting maternal health risk categories, including high, low and medium risk classes. The model achieved an overall accuracy of 0.99, indicating that 99% of all predictions were correctly classified out of 2 000 test samples.

For the high-risk class, the model achieved a precision, recall and F1-score of 1.00, meaning all high-risk cases were correctly identified without misclassification. This is critical in healthcare applications because it ensures that all patients requiring urgent attention are correctly detected.

For the low-risk class, the model achieve precision, recall and F1-score of 0.98, indicating strong and balanced performance across all risk categories.

The macro average and weighted average values 0.99 further confirm that the model performs consistently across all classes, even when class distributions are slightly different. The support values show that the dataset is balanced across the three categories (approximately 667 samples per class), which contributes to stable modelperformance.

Neonatal classification report

	precision	recall	f1-score	support
high	1.00	1.00	1.00	667
low	1.00	1.00	1.00	667
medium	1.00	1.00	1.00	666
accuracy			1.00	2000
macro avg	1.00	1.00	1.00	2000
weighted avg	1.00	1.00	1.00	2000

The neonatal classification report was generated by evaluating the neonatal model against its corresponding test set. The report provided a detailed breakdown of precision, recall and F1-score across the High, Low and Medium neonatal risk classes, confirming that the neonatal model achieved consistent and clinically reliable performance across all three risk categories. The results are consistent with those observed in the maternal model, demonstrating that the applied ANN architecture and training methodology generalized effectively to both patient groups.

4.5 Model Deployment Artefacts

Upon completion of training and evaluation, all model components required for real-time deployment were serialized and saved. The table below summarizes the deployment artefacts generated for both the maternal and neonatal predictive models.

Artefact file	**Location**	**Purpose**

Maternal_risk_model_enhanced.h5	Models/maternal/	Trained Keras model containing learned weights from best epoch
Scaler.pkl	Models/maternal/	Fitted MinMaxScaler for normalizing incoming patient input
Encoder.pkl	Models/maternal/	Fitted labelEcoder for decoding predicted integer classes
Class_labels.pkl	Models/maternal/	Dictionary mapping integer class indices to risk labels
Neonatal_risk_model.h5	models/neonatal/	Trained Keras model for neonatal feature normalization
Scaler.pkl	models/neonatal/	Fitted MinMaxScaler for neonatal class decoding
Encoder.pkl	models/neonatal/	Fitted LabelEncoder for neonatal class decoding
Class_labels.pkl	models/neonatal/	Dictionary mapping neonatal integer classes to risk labels

Table 4.1: Model Deployment Artefacts

These four artefacts collectively constitute the complete deployable model package for each model. The Flask web application loads all artefacts on startup and uses them in sequence during every real-time prediction request: the scaler normalizes the incoming patient input, the model

generates a probability distribution across the three risk classes, np.argmax() selects the class with the highest probability, and the class_labels dictionary converts the integer result into the human-readable risk label displayed to the user.

4.5.1 Flask Web Application

The trained models were integrated into a Flask-based web application, which serves as the primary user interface for the telehealth system. Flask is a lightweight Python web framework that enables rapid deployment of machine learning models as web services (Grinberg, 2018). The application provides separate dashboards for postnatal mothers, healthcare professionals and system administrators, with dedicated endpoints for real-time risk prediction, patient record management and clinical communication.

4.6 System Interface and Performance

This section presents the key interface screens developed for the telehealth system and discusses the clinical functionality supported by each component. The interface was designed in accordance with Human-Computer Interaction (HCI) principles, namely simplicity, consistency, visibility f system status and user feedback, to accommodate users across varying levels of digital literacy (Sharp et al., 2023).

4.6.1 User Registration Interface

The registration interface provides postnatal mothers and healthcare professionals with a secure account creation mechanism within the telehealth system. Users are required to supply personal details including first name, surname, phone number, age, email address and password. To strengthen security and data integrity, the system integrates input validation. The design ensures that only authorized users can create accounts and access the system’s functionalities.

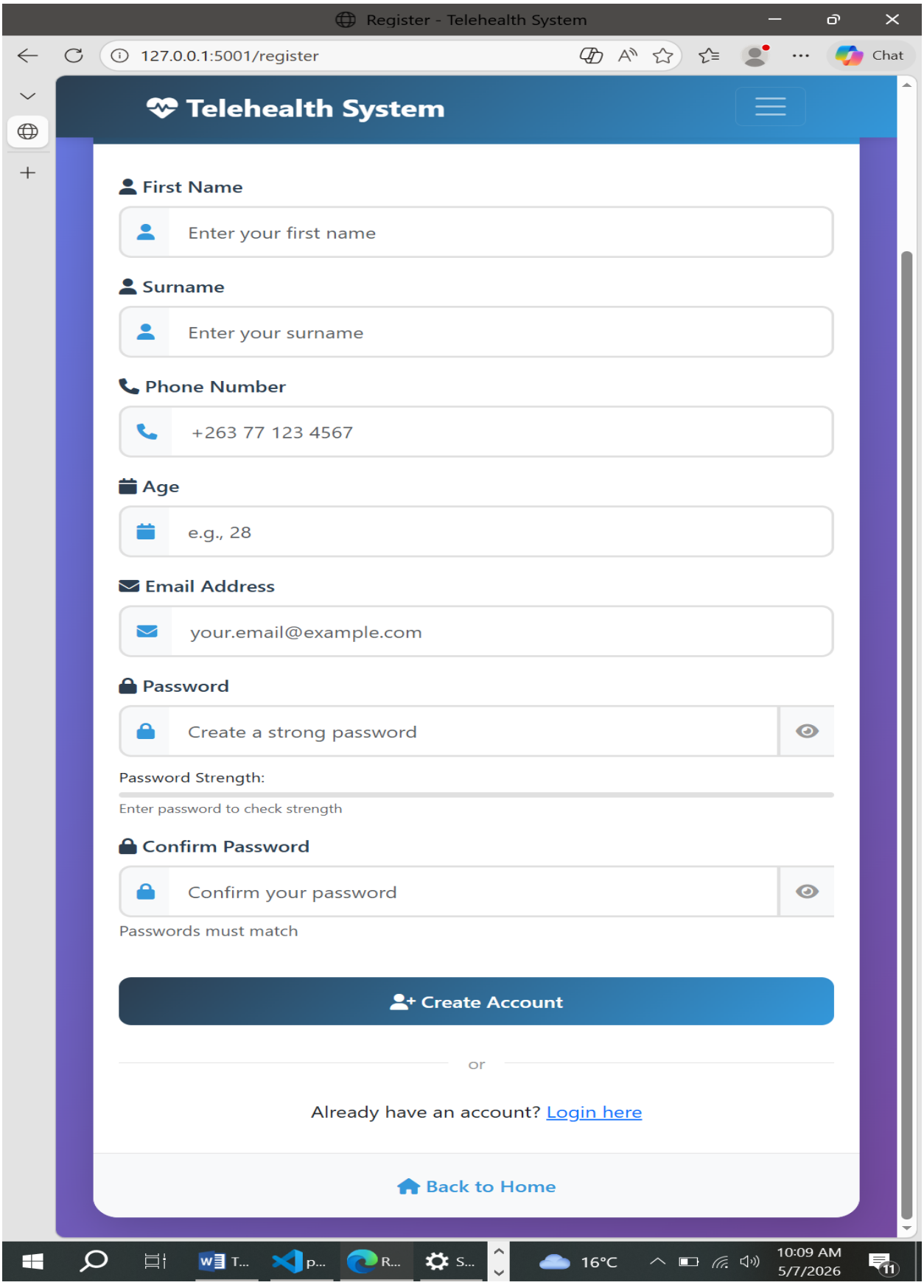

Register - Telehealth System
127.0.0.1:5001/register
Chat
Telehealth System
First Name
Enter your first name
Surname
Enter your surname
Phone Number
+263 77 123 4567
Age
e.g., 28
Email Address
your.email@example.com
Password
Create a strong password
Password Strength:
Enter password to check strength
Confirm Password
Confirm your password
Passwords must match
Create Account
or
Already have an account? Login here
Back to Home
16°C
10:09 AM
5/7/2026

Figure 15: Registration Page

4.6.2 Login Interface

The login page allows registered users to secure access the telehealth system by ensuring their email address and password, the interface verifies user credentials before granting access to the system dashboards. Security features such as password protection and input validation are implemented to prevent unauthorized access and ensure data privacy. The layout is designed to be simple and intuitive, enabling quick access to the systems functionalities.

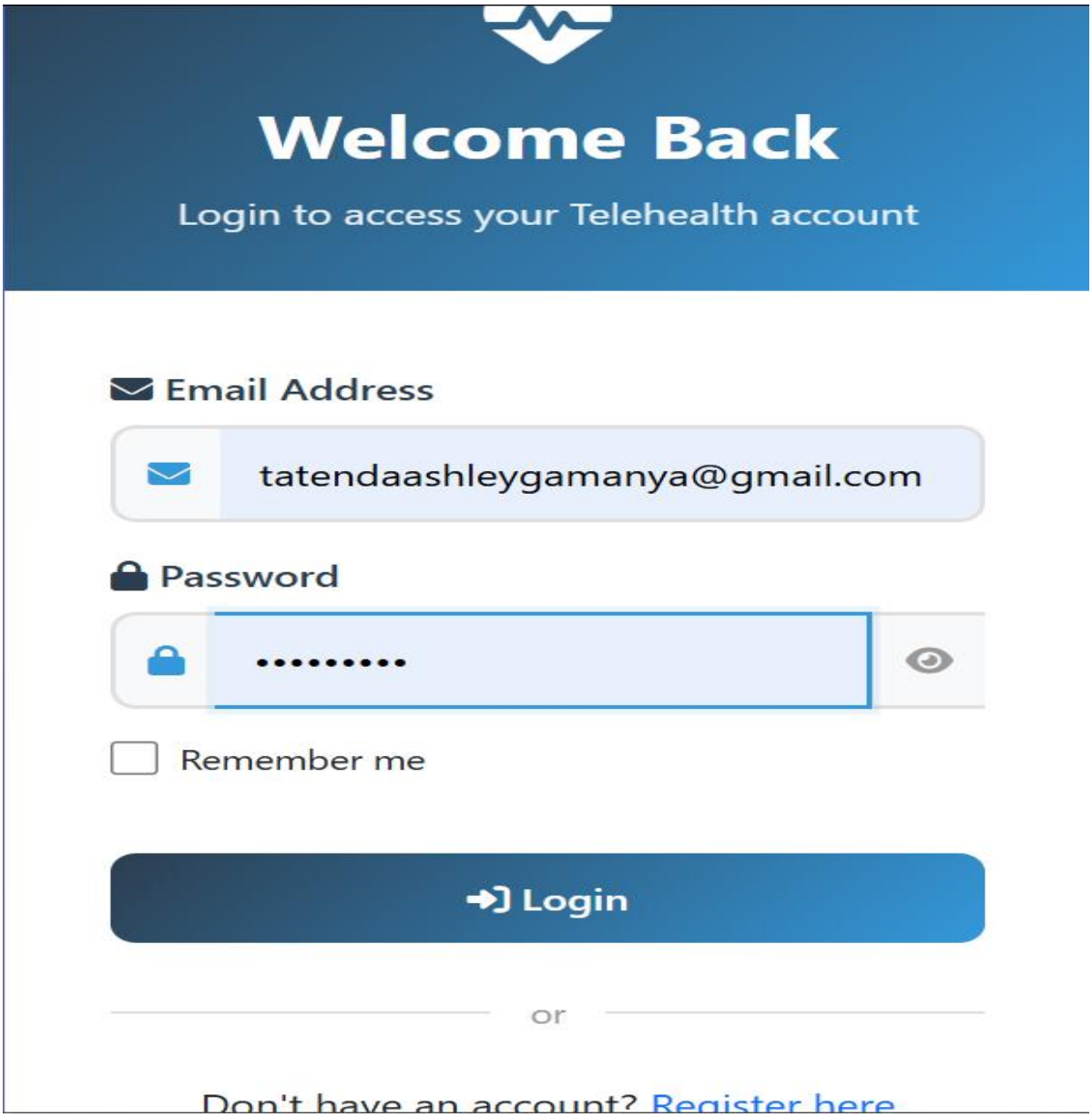


Figure 16: login page

4.6.3 Maternal Health Assessment Dashboard

The maternal health assessment dashboard allows mothers to input and monitor their health status remotely. The interface captures key maternal indicators such as blood pressure (systolic and diastolic), body temperature, heart rate and bleeding level. These inputs are used for continuous monitoring and risk prediction using the machine learning model. The dashboard includes validation rules and normal range indicators to improve accuracy and reduce incorrect data entry. The design enhances usability and supports early detection of maternal health complications.

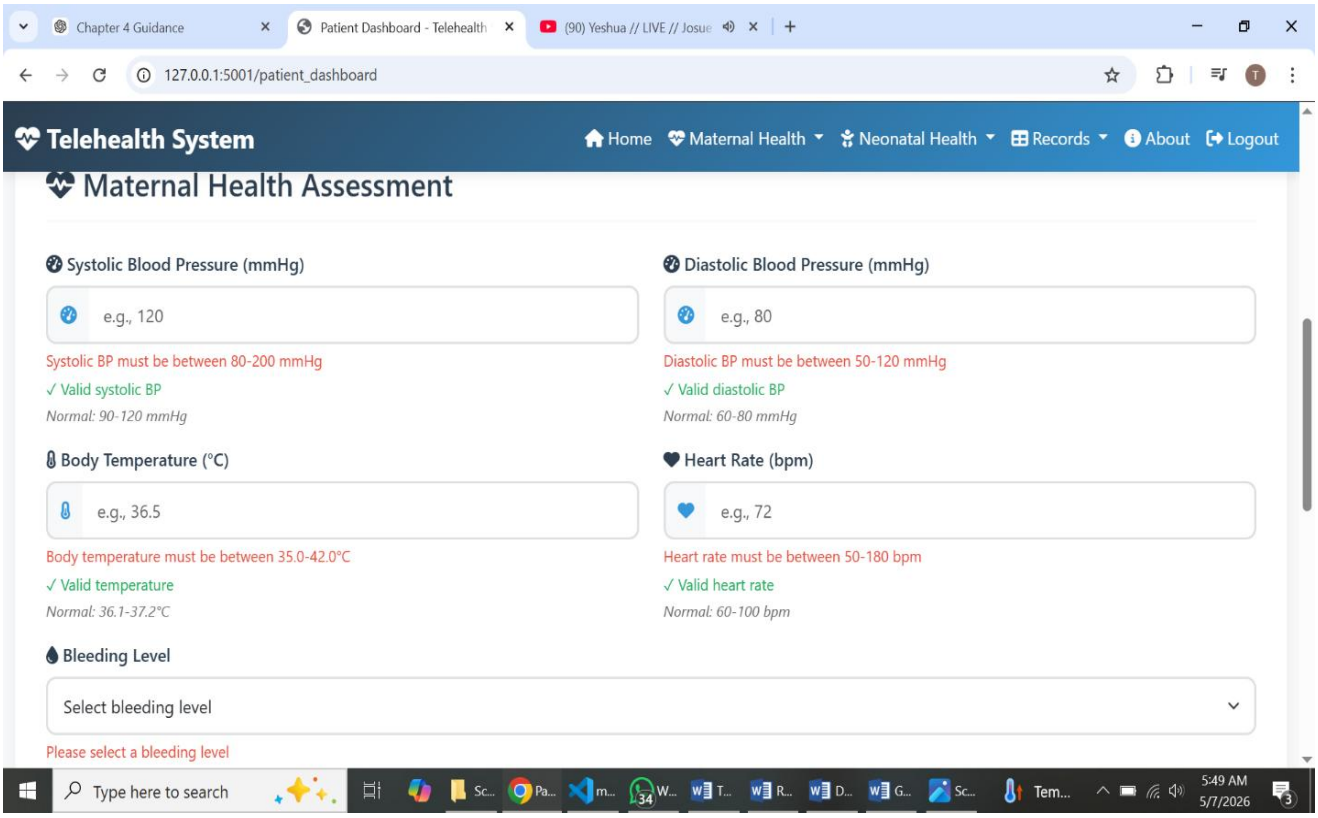


Figure 17: Maternal health assessment dashboard

4.6.4 Neonatal Health Assessment Dashboard

The neonatal heath assessment dashboard enables monitoring of newborn health conditions through the telehealth system. It collects important neonatal indicators such as birth weight, gestational age, temperature, heart rate, feeding difficult and jaundice level. The system supports early detection of neonatal health risks by allowing continuous monitoring and structured data entry. Input validation and guidance features ensure accurate recording of baby health information, improving clinical decision-making and remote healthcare support.

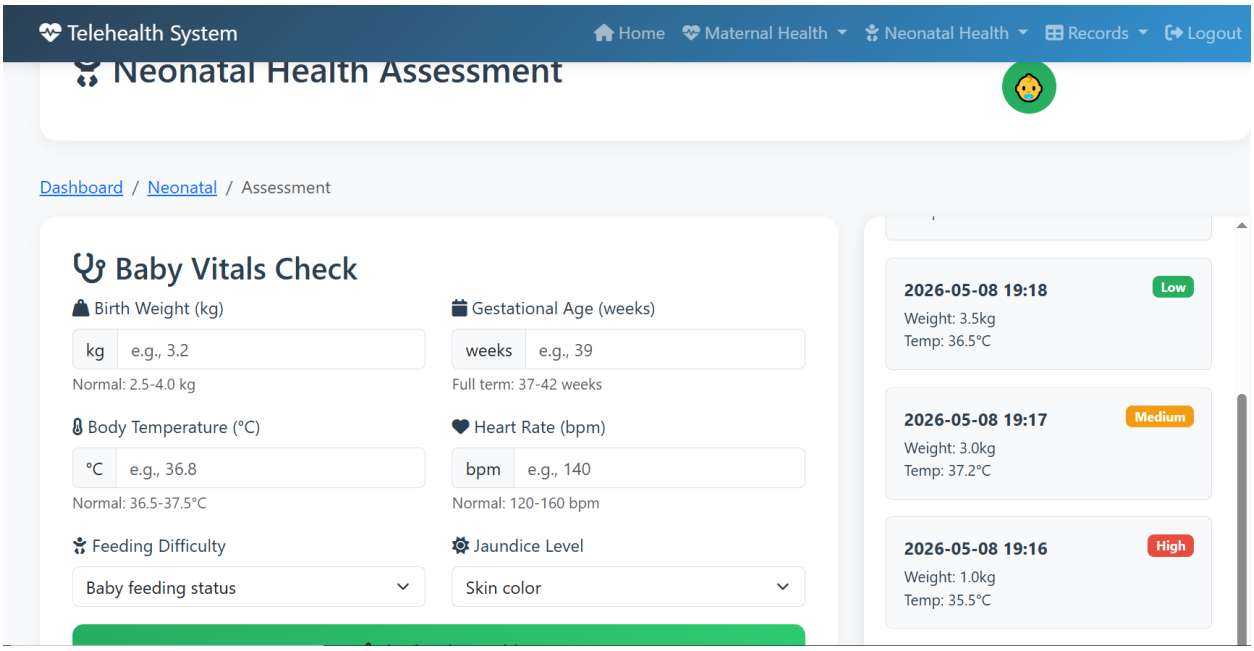


Figure 18: Neonatal health assessment dashboard

4.6.5 Administrator Dashboard

The admin dashboard provides a centralized view of system statistics, including total maternal records, neonatal records, high risk cases and overall risk rates. It allows administrators to monitor system activity and patient health trends efficiently. The dashboard also enables access to both maternal and neonatal datasets, supporting healthcare oversight users and registering new administrators, ensuring secure system control.

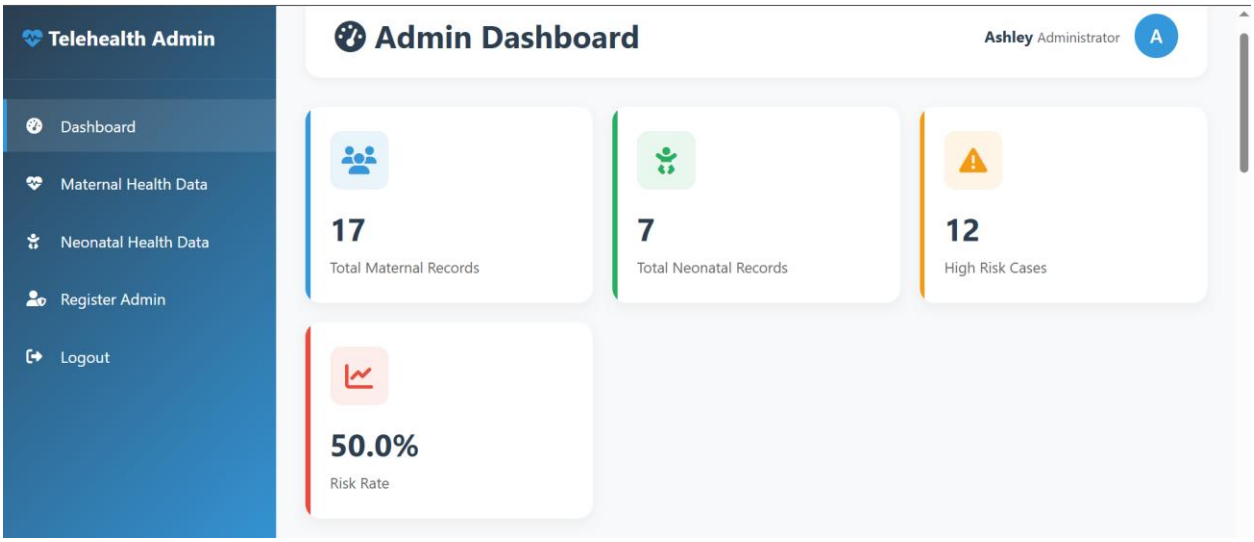


Figure 19: Admin dashboard (overview)

4.6.6 Maternal Data Module (admin view)

The maternal data module within the admin dashboard displays records in a structured tabular format. It includes clinical indicators such as blood pressure, temperature, heart rate, bleeding level, timestamps and machine learning generated risk classifications. Risk levels are displayed using color-coded indicators, red representing high risk, amber indicating medium risk and green for low risk. This visual structure supports rapid clinical decision-making and prioritization of cases.



Figure 20: Admin Dashboard (maternal data module)

4.6.7 Email Communication Interface

The email sending interface allows healthcare professionals to communicate directly with patients from within the system. When a risk is identified, clinicians can send medical advice, follow-up instruction or referrals instantly. This feature improves communication efficiency and supports teleconsultation by enabling immediate response to high-risk alerts without requiring physical hospital visits.

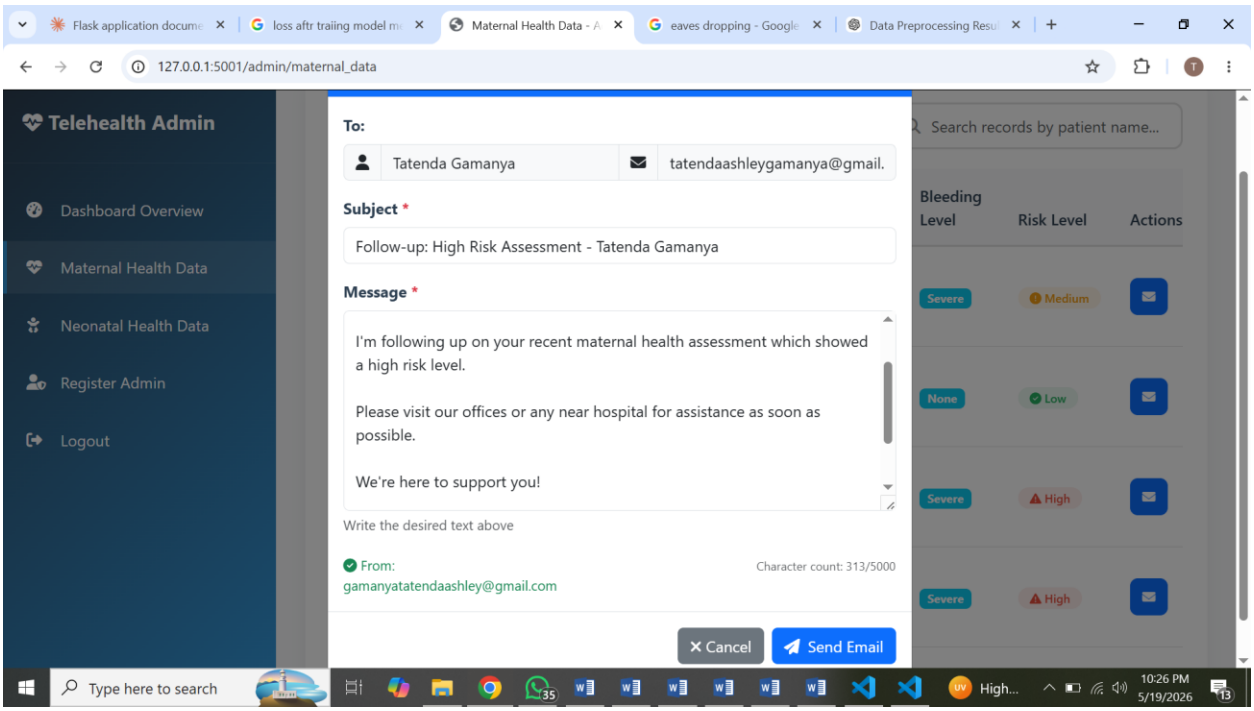
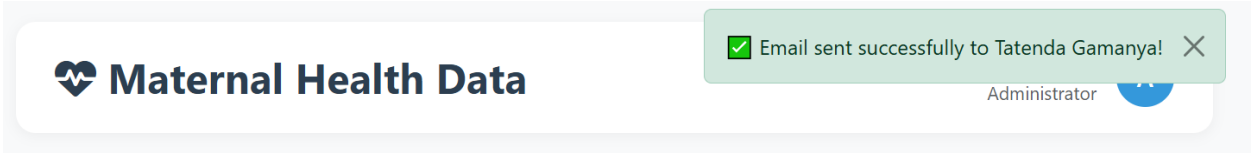


Figure 21: Email sending interface

Figure: Email sent confirmation



Upon successful message transmission, the system presents a confirmation notification to the clinician, verifying that the communication has been delivered. This confirmation step enhances system reliability and supports the documentation of clinical communication within the telehealth workflow.

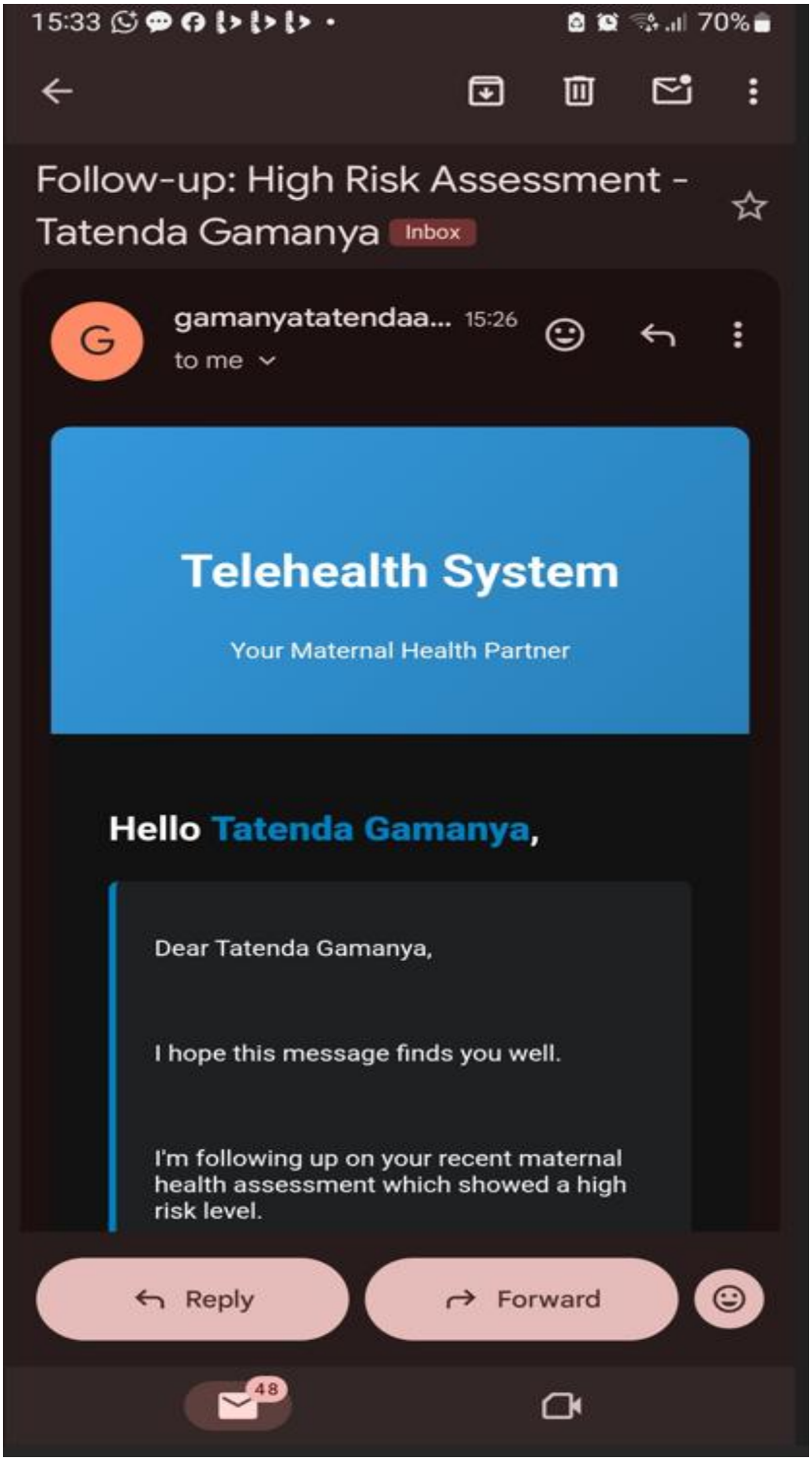


Figure 22: Email received by patient

On the patient side, the delivered email appears in the patient's inbox and contains the clinician's message regarding their health status and any recommended follow-up actions. This feature supports remote patient management by enabling mothers to receive timely clinical guidance without visiting a healthcare facility.

Why the email feature matters clinically?

1. Elimination of geographical barriers: Mothers located in remote or undeserved areas are relieved of the necessity to travel to a healthcare facility for follow-up consultations. Clinicians can contact them directly and immediately upon receiving a high-risk alert, reducing delays in clinical response.
2. Closing the clinical alert loop: In the absence of an integrated communication channel, a high-risk flag remains a passive notification with no guaranteed follow-up. The email action button transforms such alerts into actionable clinical interventions, ensuring that risk classifications prompt a concrete clinical response.
3. Generation of an auditable communication record: All clinician–patient messages transmitted through the system are automatically timestamped and logged, thereby establishing a documented trail of clinical decisions and follow-up actions that supports accountability and quality assurance and compliance with healthcare documentation standards.

4.7 Discussion

4.7.1 Model Performance

The maternal health risk prediction model achieved a test accuracy of 99%, which represents an excellent classification performance for a multi-class healthcare risk prediction task. The use of BatchNormalization, progressive Dropout regularization and adaptive learning rate callbacks contributing to this high accuracy preventing overfitting and promoting stable model convergence (Goodfellow et al., 2016). The EarlyStopping callback halted training at epoch 25 and restored the best weights from 10 where validation accuracy peaked at 99%, confirming that the training process was well controlled and did not over fit despite training for up to 150 epochs being permitted.

The neonatal model demonstrated comparably strong performance, further validating the effectiveness of the ANN architecture and training methodology when applied across different patient groups within the same clinical domain.

4.7.2 Clinical Significance of results

The high recall scores observed for the high risk class are of particular clinical importance. In postnatal monitoring, a missed high risk classification (a false negative) could result in a patient with life-threatening conditions such a postpartum hemorrhage or severe pre-eclampsia not receiving timely intervention. The models precision of 1.00 for high risk demonstrates that when the system raises a High risk alert. It is correct 99% of the time which is for overall accuracy, minimizing unnecessary clinical alarm while maintaining patient safety.

The strong performance on low risk classification with a recall of 0.99 is similarly important, as it reduces unnecessary clinical alerts and ensures that health resources at facilities such as Chinhoyi hospital are directed towards genuinely at-risk patients. The 100% confidence score on the Flask-compatible prediction test for a patient with normal vital signs further demonstrated that the model makes unambiguous decisions for clear-cut clinical cases.

4.7.3 Limitations

Despite the high accuracy achieved, several limitations should be acknowledged. The datasets used for model training were the publicly available UCI Maternal Health Risk dataset for the maternal model and a synthetically generated neonatal dataset for the neonatal model. While these datasets are clinically grounded, they remain limited in scope and may be limited in their capacity to represent the full range of the variability, distributional complexity, and clinical noise present across diverse patient populations and healthcare settings in Zimbabwe. The performance metrics reported reflect evaluation on held-out data drawn from the same distribution as the training data, and caution should therefore be exercised when generalizing these results beyond the populations represented in the dataset.

Furthermore, the systems current implementation relies on manually entered patient data, which introduces the risk of data entry errors. Future iterations of the system could incorporate automated

data capture mechanisms, such as integration with bedside monitoring devices, to improve input reliability.

Prospective validation of both models using primary clinical data from Chinhoyi provincial Hospital is essential to confirm that the reported accuracy metrics translate to real-world clinical performance. Such validation should involve collaboration with healthcare professionals to ensure that the system meets the practical requirements of postnatal care in resource-constrained settings.

4.8 Chapter Summary

This chapter presented the outcomes of the development, training, and evaluation and testing of the machine learning-based maternal and neonatal healthcare risk prediction system. The findings demonstrated that both models, the maternal ANN and neonatal ANN, achieved high classification accuracy and consistent performance across all three risk categories.

The training results showed that the models converged effectively, with validation accuracy stabilizing near 99% and loss values remaining very low (0.0381) throughout the later training epoch. Evaluation results included confusion matrices and classification reports confirmed that the models performed reliable across the high, medium and low risk classes, with particularly strong performance in identifying high risk maternal and neonatal cases, which is clinically important in postnatal care monitoring.

The Flask-compatible prediction tests further verified that the preprocessing pipeline, trained models, encoders and class label mappings functioned correctly within a real-time deployment environment. All deployment artefacts were successfully saved and organized for integration into the telehealth application, confirming the technical readiness of the machine learning component for system-level deployment.

This discussion highlighted the clinical significance of the achieved results, especially the models ability to support early identification of maternal and neonatal complications in remote monitoring settings.

Overall, the results confirmed that the proposed system is capable of providing accurate, reliable and deployable maternal and neonatal health risk prediction support within a resource-constrained telehealth environment. While also demonstrating sufficient usability and user acceptance to support progression toward broader clinical validation and deployment.

Chapter 5

5.1 Introduction

This chapter presents the conclusions drawn from the design, development and evaluation of the machine learning-enhanced telehealth system for remote monitoring at Chinhoyi Provincial Hospital, Zimbabwe. The chapter brings together the key findings from the preceding chapters, evaluates the extent to which the research objectives were achieved, reflects on the limitations encountered during the study and proposes a set of recommendations for future work. The chapter concludes with a statement of the overall contribution of this research to the field of maternal and neonatal health informatics in resource-constrained settings.

5.2 Summary of Findings

This research was motivated by the persistent challenges of high maternal and neonatal mortality in Zimbabwe, particularly in remote and undeserved communities where access to consistent postnatal healthcare is limited by geographical distance, inadequate infrastructure and shortage of skilled health workers (WHO, 2023).

The study aimed to address these challenges by designing, developing and evaluating a machine learning-enhanced telehealth system capable of performing real-time risk classification for postnatal mothers and their newborns. The resulting models were integrated into Flask-based web application, providing an accessible deployment platform for remote health monitoring.

The research followed a structured pipeline encompassing data collection, preprocessing, model design, training, evaluation and system deployment. Data preprocessing included the removal of missing values and duplicates, MinMaxScaler normalization of numerical features, LabelEncoder and one-hot encoding of categorical risk label, and stratified train-test splitting. The ANN architecture incorporated Batch Normalization, progressive Dropout regularization and adaptive learning rate scheduling, with EarlyStopping and ModelChechpoint callbacks ensuring optimal model generalization.

Evaluation results demonstrated that the maternal and neonatal ANNs achieved high classification accuracy. The maternal model attained a test accuracy of 99%, with particularly strong precision and recall on the high risk class. The neonatal model achieved comparable performance. These were supported by confusion matrices and detailed classification reports, confirming reliable and clinically meaningful risk prediction across all three risk categories.

5.2.1 Literature Review Findings

The systematic survey of existing machine learning and deep learning approaches for maternal and neonatal health risk assessment conducted in chapter 2 revealed several important limitations in the existing body of work. Most existing studies focused exclusively on either maternal or neonatal risk prediction, but both leaving a gap in integrated postnatal monitoring solutions. Many models were trained on small or geographically limited datasets that did not adequately represent the clinical diversity of sub-Saharan African patient populations accessible to patients and healthcare providers in real time. These gaps directly motivated the development of two separate, task-specific optimized models within a single integrated telehealth platform.

5.2.2 System Development findings

The web-based telehealth system was successfully developed using the Flask framework, providing an intuitive interface through which patients could submit maternal and neonatal vital signs and receive immediate, actionable risk level predictions of low, medium or high. The system implemented role-based access control distinguishing between patient and administrator accounts, a MySQL database for persistent storage of all assessment records and an automated email alert system using Flask-Mail over Gmail SMTP that notified all registered administrators whenever a high risk prediction was generated. The complete system was validated through a Flask-compatible prediction test in which a patient with normal maternal vital signs received a low risk prediction with a confidence score of 100%, confirming the end-to-end functionality of the preprocessing and inference pipeline.

5.3 Achievement of Research Objectives

The following conclusions are drawn from the research findings in direct relation to the four specific objectives and four research questions stated in chapter 1.

5.3.1 Objective 1 – Literature Review

Specific objective: To systematically survey and critically analyze existing deep learning and machine learning approaches for maternal and neonatal health risk assessment, identifying their methodological strengths, limitations, datasets used, evaluation metrics and gaps that motivate the need for two distinct optimized models.

Conclusion: This objective was fully achieved. The literature review identified that existing models were predominantly single-domain, either maternal or neonatal, and lacked integration into

operational telehealth platforms accessible to patients in real time. The review confirmed that no existing system combined both maternal and neonatal risk prediction within a single web-based application with automated clinical alert functionality. These gaps provided clear justification for the development of two separate, task-specific deep learning models as implemented in this study.

5.3.2 Objective 2 – Web-based Telehealth System

Specific objective: to develop and pilot test a web-based telehealth system that allows patients to provide input patient data seamlessly and receive real-time, actionable risk level predictions.

Conclusion: This objective was fully achieved. The Flask web application provided patients with accessible interface for submitting maternal and neonatal vital signs through structured online forms. Upon submission, the system preprocessed the input, passed it through the relevant trained model and returned an immediate risk classification of low, medium or high on the same page. The successful Flask-compatible prediction test, producing a low risk prediction with 100% confidence within 175ms, confirmed that the system delivered real-time, actionable predictions as intended. The system was accessible on any device with a web browser, making it suitable for remote monitoring in healthcare settings with limited infrastructure.

5.3.3 Objective 3 – Automated communication channel

Specific objective: to develop an automated communication integrated with the predictive models that enables timely and responsive interaction between patients and healthcare providers when high-risk assessment are identified.

Conclusion: This objective was fully achieved. The system implemented an automated email alert mechanism using Flask-Mail configured with Gmail SMTP over STARTTLS on port 587. Whenever either the maternal or neonatal prediction model classified a patient as High risk, the system automatically queried the database for all registered administrator accounts and dispatched formatted HTML alert emails to each administrator without any manual intervention. The alert emails included the patient's name, risk level and assessment details, enabling healthcare providers at Chinhoyi Provincial Hospital to respond promptly to high-risk cases identified through remote monitoring. The communication channel was tested and confirmed to function correctly during system development.

5.3.4 Objective 4: Evaluation

To evaluate the performance of the developed system using appropriate machine learning metrics.

This objective was achieved through rigorous model evaluation using accuracy, loss, confusion matrices and classification reports including precision, recall and F1-score. The maternal model achieved a test accuracy of 98.84% and a loss of 0.0381, with a precision and recall of 1.00 on the high risk class. Evaluation results confirmed that both models generalized effectively to unseen data and performed reliably across all three risk categories. Training history graphs further confirmed rapid model convergence and stability, with no evidence of overfitting (chapter 4).

5.4 Conclusion

Based on the findings of this study, the following conclusions are drawn:

5.4.1 Machine learning can provide clinically meaningful postnatal risk classification

The ANN models developed in this study demonstrated that machine learning is capable of accurately classifying maternal and neonatal health risk based on routinely collected clinical indicators. The maternal model achieved 99% test accuracy, with perfect precision and recall on the high risk class, confirming that the model can reliably identify the most critical cases without generating excessive false alarms. This level of performance is clinically significant: in postnatal care, the timely identification of high risk patients is directly linked to the prevention of life-threatening complications such as postpartum hemorrhage and severe neonatal distress (Lawn et al., 2023).

5.4.2 The system is technically deployable

The deployment artefacts generated in this study, including the trained Keras models, MinMaxScalers, LabelEncoders and class label dictionaries, constitute a complete and technically deployable prediction pipeline. The Flask web application successfully loads and applies these artefacts during real-time prediction request.

5.4.3 Integrated communication features are essential for closing the clinical alert loop

A key finding of this study is that risk prediction alone is insufficient to produce clinical impact. Without a mechanism for acting on generated risk alerts, high-risk classifications remain passive notifications. The integrated email communication feature implemented in this system transforms risk alerts into actionable clinical interventions by enabling healthcare professionals to respond

immediately to flagged cases. This design principle, that risk classification must be coupled with a structured response pathway, should inform the development of future telehealth systems in similar settings.

5.5 Recommendations

Based on the conclusions drawn from this study, the following recommendations are made for future research and development.

5.5.1 Integration with automated data capture devices

The current system relies on manual data entry by patients or healthcare workers, which introduces the risk of data entry errors and may reduce system usability in low-literacy populations. Future development should explore the integration of the telehealth system with automated data capture devices, such as digital blood pressure monitors, pulse oximeters, and smart weighing scales, which can transmit readings directly to the system through Bluetooth or Wi-Fi connectivity. Automated data capture would improve input accuracy, reduce the cognitive burden on users, and support more frequent monitoring intervals.

5.5.2 Mobile application development

While the web-based interface developed in this study is accessible via mobile browsers, the development of a dedicated mobile application for Android devices would significantly improve accessibility for postnatal mothers in Zimbabwe, where mobile phone penetration is considerably higher than desktop or laptop computer ownership (GSMA, 2023). A mobile application could also incorporate offline data capture capabilities using local storage, which would be particularly valuable in areas with unreliable internet connectivity. Captured data could be synchronizes with the central server when connectivity is restored.

5.5.3 Strengthening data privacy and security

Given that the system manages confidential patient information, maintaining strong security and privacy safeguards is critical. Future enhancements should align with the requirements of the Zimbabwe Data Protection Act (2021) and, where relevant, internationally accepted regulatory frameworks such as HIPAA and GDPR.

To strengthen data protection, the system should incorporate comprehensive security mechanisms, including encryption of transmitted data, role-based user authorization, continuous monitoring of data access activities through audit trails, and periodic assessments to identify and address potential security vulnerabilities.

5.5.4 Incorporation of explainable AI techniques

Healthcare professionals are more likely to trust and act on machine learning predictions when the reasoning behind those predictions is transparent and interpretable (Lipton, 2018). Future iterations of the system should incorporate Explainable Artificial Intelligence (XAI) techniques, such as SHapley Additive exPlanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME), to provide clinicians with feature-level explanations for each risk prediction. For example, a high risk alert could be accompanied by a display of the clinical features that most strongly contributed to that classification, enabling the clinician to make a more informed and confident clinical decision.

5.6 Final remarks

Maternal and neonatal mortality in Zimbabwe and across sub-Saharan Africa remain urgent public health challenges that cannot be resolved by clinical capacity alone. Technology, and specifically the convergence of machine learning and telehealth, offers a powerful complementary pathway for extending the reach and responsiveness of postnatal care systems to populations that are currently underserved.

This study has demonstrated that a machine learning-enhanced telehealth system for remote postnatal monitoring is technically achievable, clinically grounded, and capable of producing accurate risk classifications that are directly relevant to the clinical priorities of maternal and neonatal health. While the system requires clinical validation and further development before it can be responsibly deployed in a live healthcare setting, the results presented in this dissertation establish a solid and evidence-based foundation for that next phase of work.

It is hoped that this research contributes in a meaningfully way to the growing body of evidence supporting the use of digital health technologies in improving maternal and neonatal health outcomes in Zimbabwe and in comparable resource-constrained settings across the region.

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