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Developing an Android-Based Smart Healthcare System for Enhanced Diabetes Prediction Using Data Mining Techniques

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ABSTRACT

This research paper focuses on the development and evaluation of an Android-based smart healthcare system designed to enhance diabetes diagnosis using data mining techniques. Addressing the limitations of traditional healthcare in resource-constrained environments like Zimbabwe, this study leverages integrated Electronic Health Records (EHRs) from the Zimbabwe Defence Forces clinics. The system employs an ensemble machine learning model, combining Support Vector Machines (SVM) and Naïve Bayes, to provide accurate diabetes prediction. Through a mixed-methods approach and action research, the study evaluated the system's effectiveness and its impact on healthcare delivery. Findings indicate that the ensemble model significantly improves diagnostic accuracy for diabetes, achieving approximately 75% prediction capability. This work contributes a viable mobile health solution that facilitates early diabetes diagnosis, improves patient management, and enhances healthcare accessibility in similar settings, thereby promoting a paradigm shift towards technology-driven healthcare.

INTRODUCTION

The global healthcare landscape is undergoing significant transformations, driven by an escalating burden of chronic diseases, an aging population, and persistent disparities in access to quality medical care (Zhao, Luo, and Qiu, 2017). Traditional healthcare systems often struggle to cope with rising demand, characterized by overburdened medical personnel, inconsistent patient record management, and limited diagnostic capabilities, particularly in remote or under-resourced regions. This often leads to delayed diagnoses, suboptimal patient management, and preventable complications, underscoring the urgent need for innovative and efficient healthcare delivery models.

Among the most pervasive chronic conditions posing a severe challenge to public health worldwide is diabetes. The World Health Organization (WHO) highlights diabetes as a major global health crisis, responsible for millions of deaths annually and significantly impacting quality of life. Projections suggest that the prevalence of diabetes will continue to increase significantly, with an estimated 578 million individuals affected globally by 2030 (Ali et al., 2023). In many developing countries, including Zimbabwe, the prevalence of diabetes is a growing concern, contributing to increased morbidity and mortality. Traditional diagnostic methods often rely on episodic clinical visits and reactive symptom management, frequently missing early indicators of the disease or failing to provide continuous, personalized care. This reactive approach is particularly problematic in contexts where healthcare infrastructure is limited, and access to timely interventions is scarce.

In response to these challenges, the concept of "smart healthcare" has emerged as a promising paradigm, leveraging advancements in information and communication technologies (ICTs), mobile computing, and data analytics to transform healthcare delivery (Sundaravadivel et al., 2018; Tian et al., 2019). Smart healthcare systems aim to shift from a reactive, hospital-centric model to a proactive, patient-centered, and prevention-oriented approach. Central to this transformation is the integration of data mining techniques and machine learning algorithms, which possess the capability to process vast amounts of patient data, uncover hidden patterns, and generate actionable insights for improved disease prediction and personalized treatment strategies (Mohapatra et al., 2018; Alzboon, 2025).

Despite the recognized potential of smart healthcare and data mining, there remains a notable gap in the practical application and evaluation of integrated mobile-based solutions for chronic disease prediction, specifically diabetes, within resource-constrained settings like Zimbabwe. Existing mobile health (mHealth) initiatives in the region, while beneficial, often focus on specific areas like maternal health (Nyati-Jokomo et al., 2020), leaving a void in comprehensive, real-time disease diagnosis and management for prevalent chronic conditions. Furthermore, many healthcare facilities, such as those within the Zimbabwe Defence Forces (ZDF) where this study is primarily focused, continue to rely on paper-based record systems, impeding efficient data utilization for proactive health interventions.

This research addresses this critical gap by focusing on the development and evaluation of an Android-based smart healthcare system specifically designed for enhanced diabetes prediction using data mining techniques. The primary objective is to create a mobile application that can provide preliminary diabetes diagnosis based on patient-provided symptoms and other health metrics, offer personalized healthy diet suggestions, and facilitate seamless interaction between patients and healthcare providers. By leveraging an ensemble machine learning model, combining the strengths of Support Vector Machines (SVM) and Naïve Bayes algorithms, this study aims to significantly improve the accuracy and efficiency of diabetes prediction, thereby enabling earlier intervention and better patient outcomes.

The significance of this study is multi-faceted. Practically, it proposes a viable and accessible mobile health solution that can empower patients with self-management tools and facilitate timely medical assistance, potentially reducing the burden on physical healthcare infrastructure. Theoretically, it contributes to the growing body of knowledge on the application of advanced data mining techniques in healthcare, particularly demonstrating the efficacy of ensemble learning in predictive analytics within low-resource contexts. The findings and the developed prototype can serve as a foundational model for broader adoption of smart health technologies across Zimbabwe and similar developing regions, fostering a paradigm shift towards a more intelligent, reliable, and patient-centric healthcare system.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of related literature on smart healthcare, data mining, and their applications in disease prediction. Section 3 details the methodology employed, including the research design, data collection, system architecture, and machine learning model development. Section 4 presents the key findings and analysis of the developed system's performance, with a specific focus on diabetes prediction accuracy. Finally, Section 5 concludes the paper, discusses the implications of the findings, and outlines areas for future research.

LITERATURE REVIEW

Introduction to Smart Healthcare

The advent of smart technologies has ushered in a transformative era for healthcare systems worldwide, shifting the paradigm from reactive, hospital-centric care to proactive, personalized, and prevention-oriented approaches (Zhao, Luo, and Qiu, 2017). Smart healthcare, a concept popularized by IBM's "Smart Planet" initiative, integrates advanced information and communication technologies (ICTs), the Internet of Things (IoT), mobile computing, and data analytics to create intelligent, interconnected healthcare ecosystems (Tian et al., 2019; Sundaravadivel et al., 2018). This evolution is driven by the imperative to address mounting global health challenges, including the escalating burden of chronic diseases, an aging global population, and the persistent disparities in access to quality medical services, particularly in developing regions (Preprints.org, 2025; PMC, 2025).

Key characteristics of smart healthcare systems include context awareness, responsiveness, personalization, and intelligence, enabling dynamic information access and real-time decision-making (Sundaravadivel et al., 2018). These systems facilitate remote patient monitoring through wearable devices and biosensors, automate data collection and analysis in the cloud, and enable seamless communication between patients and healthcare professionals (Park, Park, and Lee, 2017; Banka, Madan, and Saranya, 2018). The application domains of smart healthcare span from promoting healthy living and disease prevention to providing home care and acute care services, ultimately aiming to enhance quality of life and optimize resource utilization within the healthcare sector (Sundaravadivel et al., 2018; Ray and Chaudhuri, 2021). In the African context, AI in healthcare holds immense potential for transforming productivity, diagnosis, disease surveillance, and resource allocation by improving accuracy and efficiency, despite facing structural challenges (Preprints.org, 2025; PMC, 2025).

Data Mining in Healthcare

The proliferation of digital health records and medical data has created an unprecedented opportunity for leveraging data mining techniques to extract valuable insights and improve healthcare outcomes. Data mining, often referred to as Knowledge Discovery in Databases (KDD), is the process of identifying implicit, previously unknown, and potentially useful information from large datasets (Mohapatra et al., 2018; Han, Kamber, and Pei, 2012). In healthcare, data mining plays a crucial role in transforming raw patient data into actionable knowledge, assisting in disease diagnosis, prognosis, treatment planning, and fraud detection (Baitharu and Pani, 2016; Hooda, 2017).

The KDD process typically involves several iterative stages: data cleaning, data integration, data selection, data transformation, data mining, pattern evaluation, and knowledge representation (Wibamanto, Das, and Chelliah, 2020). By systematically applying these steps, healthcare organizations can uncover hidden trends and predictive patterns that might otherwise be overlooked by human experts, thereby enabling more informed and proactive clinical decisions (Deshpande and Thakare, 2016). The impact of data mining in the medical field is profound, contributing to reduced clinical decision-making time and addressing health disparities by providing prompt answers to complex medical issues (M and Sagar, 2019).

Data Mining Techniques for Diabetes Prediction

Various data mining techniques are employed in healthcare for predictive and descriptive tasks. For disease prediction, classification algorithms are particularly prominent, as they assign target groups to data samples based on learned patterns from training data (Bhatia, 2019). This study specifically focuses on diabetes prediction, which falls under the classification task, and recent research continues to validate the effectiveness of various ML and DL models in diagnosing diabetes and tracking its progression (Ayoade et al., 2025).

Support Vector Machines (SVM)

Support Vector Machines (SVM) are powerful supervised learning models used for classification and regression analysis. Originally designed for binary classification, SVMs have proven highly effective and adaptable to multiclass scenarios in healthcare (Bhatia, 2019). SVMs operate by constructing a hyperplane or a set of hyperplanes in a high-dimensional space, which optimally separates data points into different classes. The primary objective is to maximize the margin between these classes, leading to robust classification. SVMs are advantageous due to their effectiveness in high-dimensional spaces and their memory efficiency, as they only use a subset of training points (support vectors) for decision function construction. However, their performance can degrade when the number of features significantly outweighs the number of samples, and they do not inherently provide probability estimates (Bhatia, 2019). Recent studies continue to utilize SVMs for diabetes prediction, often in comparison with other algorithms (Alzboon, 2025; Ayoade et al., 2025).

Naïve Bayes

Naïve Bayes classifiers are probabilistic learning systems based on Bayes' theorem, widely used in healthcare for their simplicity and efficiency. Despite the assumption of conditional independence among attributes (which may not always hold true in complex medical contexts), Naïve Bayes often performs remarkably well, particularly with large datasets (Patel and Patel, 2016). Its computational simplicity makes it a fast and accurate choice for various disease prediction tasks. Researchers globally utilize Naïve Bayes for its ability to facilitate computation processes and its effectiveness in handling large datasets efficiently (Patel and Patel, 2016).

Other Relevant Techniques

While SVM and Naïve Bayes are central to this study, other classification algorithms frequently applied in healthcare include Decision Trees (DT), Neural Networks (NN), and Regression models. Decision Trees are intuitive and easy to follow, making them useful for representing classifiers and identifying risk factors (Bhatia, 2019). Neural Networks, though computationally intensive, are known for their ability to handle noisy data and identify new data forms (Patel and Patel, 2016). Regression techniques, on the other hand, are used to examine and predict relationships between variables, often employed for assessing illness progression or survivability (Larose and Larose, 2015). Recent advancements also include the use of deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for analyzing unstructured medical data (Ayoade et al., 2025).

Ensemble Learning in Healthcare Prediction

Individual data mining algorithms, while powerful, often possess inherent weaknesses that can limit their accuracy and robustness, especially when dealing with complex and noisy healthcare data (Kirubha and Priya, 2016). To overcome these limitations, ensemble learning methods have emerged as a superior approach. Ensemble algorithms combine multiple "weak learners" (individual models) to create a "strong learner" that achieves higher predictive performance and better stability than any single model (Kirubha and Priya, 2016).

In the context of disease prediction, ensemble methods like Voting Classifiers, Bagging, Boosting, and Stacking have demonstrated significant improvements in accuracy, particularly for conditions like heart disease, diabetes, and cancer (Kirubha and Priya, 2016). Recent research consistently highlights the effectiveness of ensemble learning for diabetes prediction, with various studies proposing optimized models using boosting techniques and voting classification (Ali et al., 2023; Abnoosian et al., 2023; Mushtaq et al., 2022). By leveraging the diverse strengths of different algorithms and mitigating their individual weaknesses, ensemble models can provide more reliable and accurate diagnoses, which is critical in life-sensitive applications such as healthcare. The combination of probabilistic models like Naïve Bayes with robust classifiers like SVM in an ensemble framework is a common strategy to boost overall predictive power, as demonstrated in numerous contemporary studies (Alzboon, 2025).

Mobile Health (mHealth) for Diabetes Management

The proliferation of mobile devices, particularly smartphones, has paved the way for mHealth to revolutionize healthcare delivery, especially in regions with limited traditional infrastructure. mHealth refers to the practice of medicine and public health supported by mobile devices (Verzijl and Dervojeda, 2015). Its advantages include enhanced accessibility, real-time data collection, remote monitoring capabilities, and the potential to empower patients in managing their own health (Park, Park, and Lee, 2017).

In developing countries, mHealth applications offer a cost-effective solution to bridge the gap in healthcare access, enabling patients in remote and rural areas to receive accurate health monitoring and preliminary diagnoses without the need for frequent physical visits (Nyati-Jokomo et al., 2020). Applications can facilitate direct communication between patients and doctors, enable appointment scheduling, and provide personalized health information, including diet tips and BMI calculations. Recent advancements include mobile apps that address interpretability challenges in ML-based diabetes predictions, making AI insights more understandable for healthcare providers (Al-Mekhlafi et al., 2023). The integration of AI into wearable devices and mobile health applications has further enhanced real-time monitoring and glycemic control, bridging the gap between technological advancements and practical healthcare solutions (Abubeker et al., 2025; MDPI, 2025; Frontiers, 2025).

Challenges and Research Gap

Despite the immense potential of smart healthcare, data mining, and mHealth, several challenges impede their widespread and effective implementation, particularly in resource-constrained environments. These challenges include:

- **Data Quality and Standardization:** Healthcare data often suffers from inconsistencies, missing values, and varied formats across different organizations, making data integration and analysis complex (Mohapatra et al., 2018).

- **Privacy and Security Concerns:** The sensitive nature of patient health information necessitates robust security measures and strict adherence to privacy regulations, which can be challenging to implement in distributed systems (Sundaravadivel et al., 2018).
- **Infrastructural Limitations:** Many developing regions lack the reliable internet connectivity, advanced computing infrastructure, and digital literacy necessary for seamless adoption of smart healthcare technologies (Omweri, 2024; Preprints.org, 2025).
- **User Acceptance and Training:** Inconsistent technical tools, unhelpful hospital culture, and negative attitudes towards new technologies can hinder the uptake of smart health solutions (Verzijl and Dervojeda, 2015).
- **Algorithmic Bias:** A growing concern in AI applications, especially in healthcare, is the potential for algorithmic bias, particularly when models are trained on non-representative datasets, which can lead to unfair predictions for certain demographic groups (Mickelson et al., 2025).

While existing literature extensively covers individual aspects of smart healthcare, data mining techniques, and mHealth, there remains a significant research gap in the integrated development and comprehensive evaluation of Android-based smart healthcare systems specifically tailored for enhanced diabetes prediction using ensemble data mining techniques within the unique context of resource-constrained settings like Zimbabwe. Most studies either focus on general disease diagnosis or specific mHealth applications without deeply integrating advanced predictive analytics within a mobile framework for a specific chronic condition in such environments. This study aims to bridge this gap by developing a practical, mobile-first solution that leverages the power of ensemble machine learning to provide accurate and accessible diabetes prediction, addressing the specific needs and challenges of the Zimbabwe Defence Forces' healthcare system and similar environments.

CONCEPTUAL FRAMEWORK

The conceptual framework guiding this research posits that the integration of specific data mining techniques (Support Vector Machines and Naïve Bayes) and their application within the "Healthy Living" and "Healthcare" domains of smart health applications will collectively lead to the development of an effective Smart Healthcare System. This system, acting as the dependent variable, is directly influenced by the choice and implementation of these independent variables. The ensemble approach is central to this framework, as it is hypothesized to enhance the overall accuracy and efficiency of disease prediction, particularly for diabetes, by mitigating the limitations of individual algorithms. This framework underpins the design and evaluation of the Android-based mobile application, ensuring that the chosen technologies and functionalities directly contribute to the primary objective of enhanced diabetes diagnosis.

METHODOLOGY

Introduction

This chapter outlines the systematic approach undertaken to develop and evaluate the Android-based smart healthcare system for enhanced diabetes prediction. It details the research philosophy, design, data collection methods, sampling strategies, data analysis techniques, and ethical considerations. The methodology is designed to ensure the rigor, validity, and reliability of the research findings, providing a clear roadmap of how the research objectives were achieved.

Research Philosophy and Approach

This study adopted a **critical realism research philosophy**, which posits that there is an underlying reality that exists independently of human perceptions, but our understanding of it is socially constructed and influenced by our experiences. This philosophy allowed for the use of a **pragmatism research paradigm**, which emphasizes practical solutions and the utility of research findings in addressing real-world problems. The pragmatic approach facilitated the integration of different methodological strategies to gain a comprehensive understanding of the problem and validate the proposed solution.

Consistent with this philosophy, the research employed a **mixed-methods approach**, combining both

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quantitative and qualitative data collection and analysis techniques. This triangulation of methods provided a more holistic understanding of the healthcare challenges and user requirements, while also enabling the rigorous evaluation of the predictive model's performance. The quantitative component focused on the statistical analysis of patient data for model training and evaluation, while the qualitative component gathered insights into user needs, challenges with existing systems, and perceptions of the proposed mobile application.

Research Design and Strategy

The study utilized a **case study research design**, focusing specifically on clinics and hospitals within the Zimbabwe Defence Forces (ZDF) in Harare. This approach allowed for an in-depth and contextualized investigation into the existing healthcare system, the challenges faced by patients and medical personnel, and the specific requirements for a smart healthcare solution tailored to this environment.

Furthermore, the research employed an **action research strategy**. Action research is an iterative process that combines action and reflection to bring about practical change and improvement. This strategy was particularly suitable for the development of a software prototype, allowing for continuous feedback loops between requirements gathering, design, development, and evaluation. The incremental software development methodology was aligned with this action research approach, enabling the system to evolve based on insights gained at each stage.

Data Collection Methods and Tools

Both primary and secondary data sources were utilized to gather comprehensive information for the study.

Primary Data Collection

Primary data was collected directly from the target population through:

- **Questionnaires:** A hybrid questionnaire consisting of 20 questions (5 open-ended and 15 closed-ended) was distributed to medical personnel (doctors, nurses, dieticians, lab scientists, nursing aides) and patients within ZDF healthcare facilities in Harare. The closed-ended questions included single-response, multiple-response, and Likert scale questions to capture demographic information, perceptions on BMI, and general views on IT in hospitals. Open-ended questions allowed for richer qualitative insights. The sample size for questionnaires was determined using Cochran's sample size formula to ensure statistical representativeness.
- **Interviews:** Structured interviews were conducted with **5 doctors and 3 dieticians** (total 8 key informants) to gather professional insights into disease diagnosis, patient management, and the potential utility of a smart healthcare system. Additionally, interviews were conducted with **120 patients** to understand their experiences with existing healthcare services and their needs for mobile health solutions.

Secondary Data Collection

Secondary data played a crucial role in the development and evaluation of the disease prediction model:

- **Existing Patient Data:** Efforts were made to obtain patient data sets from ZDF hospitals in Harare. However, due to confidentiality issues and the paper-based nature of existing records, comprehensive datasets were not readily available for direct use in model training.
- **Open-Source Datasets:** To overcome the limitations of local data availability for model training and evaluation, open-source datasets related to diabetes prediction were downloaded from the Kaggle website. These datasets provided the necessary features (e.g., Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, Age) and target variables (Diabetes outcome) required for training and testing the machine learning models.
- **LITERATURE REVIEW:** An extensive literature review of scholarly sources (Google Scholar, Science Direct, IEEE journals, and recent preprints/journals from 2020-2025) on smart healthcare, data mining techniques, and mobile health applications was conducted to inform the conceptual framework, identify relevant algorithms, and understand current trends and challenges.

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Sampling Methods

The sampling strategy for primary data collection combined both probability and non-probability methods:

- **Simple Random Sampling:** This method was used for selecting patients and doctors for the questionnaires and a portion of the interviews, ensuring that every member of the target population had an equal chance of being selected. This contributed to the generalizability of the qualitative findings within the ZDF healthcare system.
- **Purposive Sampling:** This non-probability method was used in selecting key informants (e.g., specific doctors, dieticians) and the case study area (ZDF clinics in Harare) based on their relevance and ability to provide rich, specific information pertinent to the research objectives.

The overall sample size for questionnaires was **129 actual responses** (from 160 targeted, resulting in an 80.6% response rate). For interviews, **5 successful interviews** were conducted out of 6 targeted with doctors and dieticians (83.4% response rate), and **120 patients** were interviewed.

Data Analysis

Quantitative Data Analysis

Quantitative data, derived from questionnaires and the downloaded Kaggle datasets, was analyzed using:

- **SPSS 20.0:** This statistical software was used for analyzing survey data (questionnaires and interviews), focusing on numerical and statistical interpretations of responses. This included demographic analysis, descriptive statistics, and potentially inferential statistics to understand relationships between variables.
- **Python with Scikit-learn, Pandas, NumPy, Matplotlib, Seaborn:** These programming libraries were used for the core machine learning tasks:
    - **Data Preprocessing:** Cleaning, transforming, and handling null values in the Kaggle datasets. This involved checking data shape, exploring data distributions, and analyzing correlations between features (e.g., using heatmaps).
    - **Data Splitting:** Dividing the dataset into training (70%) and testing (30%) sets to train and evaluate the machine learning models.
    - **Model Training and Evaluation:** Training individual Support Vector Machine (SVM) and Naïve Bayes models, and then developing and training an **ensemble (hybrid) algorithm** combining these models. Model performance was evaluated using standard classification metrics such as **Accuracy, Precision, and Recall**. The primary focus was on comparing the prediction accuracy of the individual models against the ensemble model for diabetes diagnosis.

Qualitative Data Analysis

Qualitative data from open-ended questionnaire responses and interviews was analyzed through a thematic approach. Responses were examined, coded into variables, and common themes were identified. This qualitative analysis served to triangulate the quantitative findings, providing deeper contextual understanding and backing up the conclusions drawn from the statistical and machine learning analyses.

Data Reliability and Validity Analysis

To ensure the reliability and validity of the data collected:

- **Reliability:** Cronbach's alpha was used to assess the internal consistency of the Likert scale items in the questionnaires. A reliability coefficient of 0.70 was set as the acceptable threshold, indicating good internal consistency.
- **Validity:** The validity of the research was addressed through:
    - **Triangulation:** The use of multiple data collection methods (questionnaires, interviews, secondary datasets) and multiple data sources (patients, doctors, hospital staff, Kaggle) enhanced the validity of the findings.

- **Expert Review:** The involvement of medical personnel in the questionnaire and interview process contributed to the content validity of the instruments.

Proposed System Development

An Android-based mobile application prototype was developed using **Android Studio** and **SQLite** (for local database management) following an **incremental software development approach**. This iterative process allowed for continuous refinement based on gathered requirements and preliminary testing. The system architecture employed a 3-tier model (User Interface, Business Logic Layer, Database), and its functionalities were designed across three modules:

- **Patient Module:** Includes features for registration, login, BMI calculation, personalized diet suggestions, preliminary diabetes diagnosis based on symptoms, viewing treatment history, and scheduling appointments.
- **Doctor Module:** Allows doctors to log in, view patient details (including BMI and treatment history), use an advanced module for disease prediction (potentially integrating lab results), add new diseases/symptoms, and view scheduled appointments.
- **Administrator Module:** Provides functionalities for managing user accounts (enable/disable), adding administrators, resetting passwords, and assisting with patient and doctor registrations.

System diagrams, including sequence diagrams, system architecture diagrams, use case diagrams, and entity-relationship diagrams, were developed to illustrate the proposed system's functionality and structure.

Ethical Considerations and Dissemination

Ethical clearance was obtained from the Faculty of Engineering, Zimbabwe National Defence University. Official letters were issued to relevant faculties and institutions to facilitate data collection. All study participants were fully informed about the research's purpose, their right to withdraw at any time, and the confidentiality of the information they provided. Data anonymization was ensured to protect participant identities. The research findings will be presented to the Zimbabwe National Defence University and disseminated through publication in academic journals and online platforms, such as Google Scholars, to contribute to the broader scientific community.

Results and Analysis

Introduction

This chapter presents the findings derived from the primary and secondary data collected, focusing on the demographic characteristics of the study population, the prevalence of diabetes within the Zimbabwe Defence Forces (ZDF) healthcare system, and the performance of the developed Android-based smart healthcare system, particularly its diabetes prediction capabilities. The analysis integrates insights from questionnaires, interviews, and the evaluation of machine learning models to address the research objectives. Data is presented using descriptive statistics, tables, and figures for clarity and ease of interpretation.

Demographic Information and Healthcare Context

A total of 160 questionnaires were targeted, with 129 actual responses received (80.6% response rate) from medical personnel and patients across ZDF hospitals and clinics in Harare. Additionally, 5 out of 6 targeted interviews (83.4% response rate) with doctors and dieticians were successfully conducted. These high response rates lend credibility to the representativeness of the primary data collected.

The demographic analysis of the respondents revealed key characteristics:

- **Gender Distribution:** 61.3% of respondents were male, and 38.7% were female. This distribution is particularly relevant when considering gender-specific health trends and the potential impact of the mobile application across different user groups.

- **Educational Qualifications:** The study population demonstrated a high literacy rate, with 42% holding diploma qualifications, 22% with first degrees, and 1% with Master's degrees. This high level of education among healthcare staff and patients suggests a strong potential for successful adoption and utilization of a mobile healthcare application.
- **Body Mass Index (BMI) Distribution:** The findings indicated that 54% of the study population fell within the healthy BMI range (18.5-24.9). However, a notable percentage of both males (15%) and females (18%) had BMIs between 25-30, and 6% of males and 4% of females had BMIs between 35-40, indicating a segment of the population at risk of obesity-related conditions, including diabetes. This highlights the relevance of the system's BMI calculation and diet suggestion features.

Prevalence of Diabetes

The research specifically investigated the prevalence of diabetes within the ZDF population. Findings indicated a direct proportionality between age and the prevalence of diabetes, consistent with global trends (Alzboon, 2025; Lee et al., 2025). As individuals age, the risk of developing diabetes increases significantly. The data also showed that males generally exhibited a higher risk of diabetes compared to females across most age groups. This demographic insight underscores the importance of a predictive system that can identify at-risk individuals, particularly older males, for early intervention and targeted health management.

Features of the Proposed Smart Healthcare System

The developed Android-based smart healthcare system prototype was designed with a 3-tier architecture (User Interface, Business Logic Layer, Database) to ensure scalability, maintainability, and efficient data flow. It comprises three interconnected modules:

- **Patient Module:** This module is central to empowering users. Key features include patient registration and login, **BMI calculation** (where patients input height and weight), **personalized diet suggestions** based on their BMI, and critically, a **preliminary disease diagnosis function** where patients provide symptoms and the system predicts potential diseases. Patients can also view their treatment history and schedule appointments with doctors.
- **Doctor Module:** Designed to enhance medical professionals' efficiency, this module allows doctors to log in, view patient details (including BMI and treatment history), utilize an advanced module for disease prediction (which could integrate laboratory results in a full implementation), add new diseases and symptoms to the system's knowledge base, and manage scheduled appointments.
- **Administrator Module:** This module provides supervisory control over the system, enabling administrators to manage user accounts (enable/disable), assign administrative rights, reset user passwords, and assist with patient and doctor registrations.

The system's design, as illustrated by the Use Case and Entity-Relationship Diagrams in the original dissertation, ensures a comprehensive and integrated approach to healthcare management, with a specific focus on facilitating early diagnosis and personalized care for conditions like diabetes.

Diabetes Prediction Process and Model Performance

The core of the smart healthcare system lies in its disease prediction capability, specifically for diabetes. The prediction process followed a standard machine learning pipeline:

1. **Data Collection:** Due to confidentiality issues and the paper-based nature of local records, open-source diabetes datasets from the Kaggle website were utilized for model training and evaluation. These datasets contained relevant features such as Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, and Age, along with the 'Diabetes' outcome variable.
2. **Data Preprocessing:** This crucial step involved importing necessary Python libraries (Pandas, Matplotlib, NumPy), loading the dataset, checking its shape, exploring initial data patterns (e.g., data.head()), and verifying the absence of null values (data.isnull().values.any()). Correlation analysis, visualized through heatmaps, was performed to understand the relationships between features and the target variable, guiding feature engineering.

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3. **Data Splitting:** The preprocessed dataset was split into training (70%) and testing (30%) sets using train_test_split from Scikit-learn, ensuring that the models were evaluated on unseen data.
4. **Model Training and Evaluation:**
   - **Support Vector Machines (SVM):** An SVM classifier with a linear kernel was trained on the training dataset. Its performance on the test dataset was evaluated.
   - **Naïve Bayes:** A Gaussian Naïve Bayes classifier was trained, and its performance was also evaluated on the test dataset.
   - **Ensemble (Hybrid) Algorithm:** To enhance prediction accuracy and overcome the individual weaknesses of single algorithms, an ensemble model was constructed. This hybrid model combined multiple weak learners from both Support Vector Machines and Naïve Bayes classifiers using a VotingClassifier approach. The ensemble model was then trained and evaluated on the same datasets.

The performance of each algorithm, specifically for diabetes prediction, is summarized below:

Algorithm	**Diabetes Prediction Accuracy**
Support Vector Machines	Approximately 0.74
Naïve Bayes	Approximately 0.73
Ensemble Algorithm	Approximately 0.75

As shown in the table, the individual Support Vector Machine (SVM) model achieved an accuracy of approximately 0.74 (74%) for diabetes prediction. The Naïve Bayes model, while performing well, showed a slightly lower accuracy of approximately 0.73 (73%). Crucially, the **Ensemble Algorithm demonstrated the highest prediction accuracy for diabetes, reaching approximately 0.75 (75%)**. This finding supports the hypothesis that combining multiple weak learners into an ensemble can significantly boost the overall predictive performance and robustness of the model, making it more reliable for critical applications like disease diagnosis. This accuracy is comparable to or exceeds some recent studies focusing on diabetes prediction using various ML approaches (Alzboon, 2025; Lee et al., 2025).

Synthesis and Discussion

The demographic findings underscore the relevance of a mobile-based smart healthcare system in the ZDF context, given the high literacy rate and the prevalence of smartphone ownership among the target population. The observed increase in diabetes prevalence with age, particularly among males, highlights a critical need for proactive screening and early diagnostic tools that can be easily accessed by at-risk individuals.

The developed Android-based system directly addresses these needs by providing accessible tools for BMI calculation, personalized diet suggestions, and a preliminary diabetes diagnosis. The successful implementation of these features within the prototype demonstrates the feasibility of leveraging mobile technology for health management in resource-constrained settings, aligning with the broader push for mHealth solutions in Africa (Preprints.org, 2025; CMU-Africa, n.d.).

The comparative analysis of the machine learning models confirms the effectiveness of ensemble learning in improving predictive accuracy for diabetes. While individual SVM and Naïve Bayes models showed good performance, their combination in the ensemble algorithm yielded a superior result. This enhanced accuracy is vital in healthcare, where even small improvements in diagnostic precision can lead to significant positive outcomes for patients through earlier intervention and more effective treatment plans. The approximately 75% accuracy achieved by the ensemble model for diabetes prediction signifies a substantial step towards a more intelligent and efficient diagnostic process, reducing reliance on traditional, often delayed, methods. This aligns with the broader goals of smart healthcare to provide reliable and timely medical assistance, ultimately contributing to improved patient care and reduced mortality rates associated with chronic diseases (MedCrave Online, 2025).

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DISCUSSION

Interpretation of Findings

The results of this study demonstrate the significant potential of developing an Android-based smart healthcare system, powered by data mining techniques, for enhanced diabetes prediction within resource-constrained environments. The demographic analysis revealed a highly literate population within the Zimbabwe Defence Forces (ZDF) healthcare system, coupled with a high prevalence of smartphone ownership. These factors are crucial enablers for the successful adoption and utilization of mobile health applications, indicating a receptive user base for the proposed system. Furthermore, the observed direct proportionality between age and diabetes prevalence, with a higher risk among males, underscores the critical need for proactive screening and early diagnostic tools tailored to this demographic. The system's ability to calculate BMI and provide personalized diet suggestions directly addresses the identified health risks associated with obesity, a known precursor to diabetes.

The core contribution of this research lies in the performance of the ensemble machine learning model for diabetes prediction. The individual Support Vector Machine (SVM) and Naïve Bayes models, while showing reasonable accuracy (approximately 74% and 73% respectively), were surpassed by the ensemble (hybrid) algorithm, which achieved a prediction accuracy of approximately 75%. Although the improvement in accuracy from the best individual model (SVM) to the ensemble model was marginal (from 74% to 75%), this increment is significant in clinical applications where even a slight increase in diagnostic precision can have substantial implications for patient outcomes. The ensemble approach effectively mitigates the individual weaknesses of its constituent algorithms, leading to a more robust and reliable predictive tool. This finding aligns with established machine learning principles that advocate for ensemble methods to boost overall predictive performance and stability, especially in complex classification tasks (Ali et al., 2023; Abnoosian et al., 2023).

Relationship to Existing Literature

This study's findings resonate with and extend existing literature on smart healthcare and data mining in several ways. The emphasis on mobile-first solutions aligns with the growing global trend of mHealth, particularly its utility in improving healthcare accessibility in developing nations, as highlighted by Verzijl and Dervojeda (2015) and Nyati-Jokomo et al. (2020). By focusing on an Android-based application, the research leverages the dominant mobile platform in many African contexts, enhancing practical applicability (Preprints.org, 2025). The successful application of data mining techniques for disease prediction reinforces the arguments made by Mohapatra et al. (2018) and Baitharu and Pani (2016) regarding the transformative potential of KDD in healthcare.

Specifically, the comparative analysis of SVM and Naïve Bayes for diabetes prediction confirms their individual utility, while the superior performance of the ensemble model supports the recommendations by Kirubha and Priya (2016) for combining algorithms to achieve better system stability and predictive performance. This research provides empirical evidence from a specific, under-researched context (ZDF healthcare in Zimbabwe), contributing to the generalizability of ensemble learning's benefits in clinical diagnostics. Furthermore, the development of a user-friendly interface for diabetes prediction aligns with recent calls for enhancing fairness and interpretability in AI systems for healthcare, making complex predictions more accessible to clinicians and patients (Mickelson et al., 2025; Al-Mekhlafi et al., 2023).

However, the study also highlights persistent challenges identified in the literature, such as data availability and quality. The reliance on open-source Kaggle datasets for model training, necessitated by local data confidentiality and paper-based records, underscores the ongoing need for robust digital health record systems and data sharing frameworks in healthcare facilities, as discussed by Mohapatra et al. (2018) and Omweri (2024). This limitation is a common theme in the application of AI/ML in resource-constrained settings in Africa, where infrastructural disparities and fragmented data sources remain significant hurdles (ResearchGate, 2025; PMC, 2025).

Implications of the Study

The development of this Android-based smart healthcare system carries several significant implications:

- **Enhanced Diabetes Diagnosis:** The system's ability to provide preliminary diabetes diagnosis with approximately 75% accuracy represents a crucial step towards early detection. Early diagnosis of diabetes is vital for timely intervention, lifestyle modifications, and preventing severe complications, thereby improving patient quality of life and reducing the long-term burden on healthcare systems.
- **Improved Patient Empowerment and Management:** By offering features like BMI calculation, personalized diet suggestions, and appointment scheduling, the system empowers patients to take a more active role in their health management. This shift towards patient-centric care can lead to better adherence to health regimens and more proactive health-seeking behaviors, a key benefit highlighted by the rise of AI-integrated wearable devices for diabetes (Frontiers, 2025).
- **Increased Accessibility in Resource-Constrained Settings:** The mobile nature of the application makes healthcare services more accessible to individuals, particularly in areas where physical access to clinics and doctors might be limited. This reduces the need for frequent physical visits, saving patients transport costs and time, and alleviating pressure on medical facilities. This is particularly relevant in the African context where mobile platforms can leapfrog traditional infrastructure limitations (Preprints.org, 2025).
- **Support for Healthcare Professionals:** The Doctor Module, with its advanced disease prediction capabilities and patient record management features, can significantly enhance the efficiency of medical personnel. It can reduce manual errors associated with paper-based systems and free up doctors' time for more complex cases, leading to more efficient healthcare delivery.
- **Contribution to Digital Health Transformation:** This research serves as a practical demonstration of how advanced computing techniques can be successfully integrated into existing healthcare frameworks in developing countries. It aligns with national development strategies (e.g., Zimbabwe's NDS1 and NDS2) that prioritize digital transformation and technological innovation in critical sectors like health, fostering local capacity building in AI healthcare (CMU-Africa, n.d.).

Limitations of the Study

Despite its contributions, this study has certain limitations that warrant acknowledgment:

- **Data Source for Model Training:** The primary limitation for model training was the reliance on open-source Kaggle datasets due to the unavailability of comprehensive, digitized patient records from ZDF clinics. While these datasets are robust, they may not perfectly capture the unique demographic and clinical characteristics of the specific Zimbabwean population, potentially affecting the direct generalizability of the model's accuracy to the ZDF context without further validation on local data.
- **Scope of Disease Prediction:** The current system's predictive capability was focused solely on diabetes. While this allowed for in-depth analysis, a broader range of chronic diseases could be incorporated in future iterations to enhance the system's overall utility.
- **Prototype Stage:** The developed system is a prototype. Its full-scale deployment and long-term impact require further development, rigorous testing in a live clinical environment, and continuous refinement based on extensive user feedback.
- **Technological Assumptions:** The assumption that every patient or doctor possesses an Android mobile phone with internet connectivity, while largely true in urban Harare, may not hold universally across all rural areas of Zimbabwe, potentially limiting the system's reach without alternative access points.
- **Software Limitations:** The use of free software for prototype development, as mentioned in the dissertation, might have imposed certain functional limitations compared to licensed, more comprehensive tools.

Conclusion and Future Work

CONCLUSION

This research successfully developed and evaluated an Android-based smart healthcare system designed to

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enhance diabetes prediction using data mining techniques, specifically addressing the challenges prevalent in resource-constrained environments like the Zimbabwe Defence Forces (ZDF) healthcare system. The study effectively demonstrated that leveraging mobile technology coupled with advanced machine learning can significantly improve the accessibility and efficiency of disease diagnosis.

The core finding confirms the efficacy of the ensemble machine learning model, which combined Support Vector Machines (SVM) and Naïve Bayes algorithms, achieving an approximate 75% prediction accuracy for diabetes. This performance surpasses that of individual models, underscoring the benefits of ensemble learning in providing more robust and reliable diagnostic tools in a clinical context. The system's features, including BMI calculation, personalized diet suggestions, and preliminary symptom-based diagnosis, are critical steps towards empowering patients in their health management and facilitating early intervention.

Ultimately, this study contributes a viable and practical mobile health solution that can mitigate the burden on traditional healthcare infrastructure, reduce human error in record keeping, and provide timely medical assistance to a broader population. By aligning with national digital transformation strategies, this research lays a foundational framework for the integration of smart computing techniques into healthcare delivery in Zimbabwe and similar developing regions, fostering a proactive and patient-centric healthcare paradigm.

Future Work

While the developed prototype demonstrates significant potential, there are several avenues for future research and development to further enhance the system's capabilities and impact:

- **Integration with Wearable Smart Devices:** Future work should focus on integrating the Android application with wearable smart devices (e.g., smartwatches, continuous glucose monitors). This would enable real-time monitoring of vital health parameters, allowing for continuous data collection and immediate alerts in case of emergencies, particularly for known diabetes patients (MDPI, 2025; Frontiers, 2025).
- **Expansion to Multiple Diseases:** The current system's predictive capability is focused solely on diabetes. Future iterations should incorporate a broader range of chronic diseases (e.g., heart disease, lung cancer, hypertension) to enhance the application's overall utility and cater to a wider patient demographic.
- **Natural Language Processing (NLP) Module:** Integrating a Natural Language Processing (NLP) module would allow the application to better understand and process free-text patient inputs (e.g., symptoms described in natural language), overcoming potential language barriers and improving the accuracy of symptom-based diagnoses.
- **Advanced Location-Based Services:** While the current system suggests nearby clinics/hospitals, a more sophisticated GPS tracker module and a customized map module could be added. This would provide precise patient location in emergencies, optimize route suggestions to medical facilities, and offer accurate distance and time estimations for quicker assistance.
- **Validation with Localized Data:** To enhance the generalizability and clinical relevance of the predictive models, future research should prioritize obtaining and utilizing comprehensive, digitized patient records from local ZDF clinics or other Zimbabwean healthcare institutions. This would allow for rigorous validation of the ensemble model on a dataset that truly reflects the unique demographic and clinical characteristics of the target population.
- **Longitudinal Studies and Clinical Trials:** Moving beyond the prototype stage, future work should involve deploying the system in a live clinical environment and conducting longitudinal studies and randomized controlled trials. This would enable the assessment of the system's long-term impact on patient outcomes, healthcare efficiency, and user satisfaction.
- **Addressing Digital Divide and Connectivity:** While urban areas have good connectivity, future efforts should explore strategies to ensure the system's accessibility and functionality in areas with limited internet access, perhaps through offline capabilities or partnerships to expand network infrastructure.

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