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# Development of a hospital management system leveraging support vector machine technique

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## ABSTRACT

Healthcare institutions are extensively faced with challenges including ineffective patient record administration, dependence on hand made operational assessment, delay decision-making, and challenge evaluate to automated devices that assist clinical decision-making. Conventional hospital administration systems are complicated designed to address administrative operations and often lack complex forecast attributes that allow healthcare professionals to detect potential health dangers and provide timely interventions for strong-risk patients. The study proposed to development a web-based Hospital Management System (HMS) application leveraging Support Vector Machine (SVM) technique to facilitate the efficiency, accuracy and dependability in healthcare management processes. This developed model attained accuracy of 84.42%, precision value of 81.25%, recall rate of 86.11%, and F1-score of 83.61%. All these shows that embedding Machine Learning (ML) techniques into HMS can improve patient risk forecasting and promoting timely, data-driven clinical decision-making. The study infers that the presented system offers an effective model for automated healthcare administration and gives a foundation for the implementation of future artificial intelligence (AI) based healthcare solutions.

## KEYWORDS

Hospital management system; Support vector machine; Machine learning; Patient risk prediction; Healthcare informatics

## ARTICLE HISTORY

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## Introduction

Healthcare institutions have undergone transformative technological transformation in recent decades, with information systems becoming growing, critical information are needed for enhancing healthcare service delivery, improving patient care outcomes, and streamlining operational evaluation.

HMS have become vital concepts in the management and coordination of healthcare operations, assisting functions like patient registration, appointment management, billing processes, electronic medical record handling, and report generation. These applications assist reduce management workload, enhance the availability and accessibility of clinical information, and facilitate general performance and effectiveness of clinical institutions.

Despite these technological transformation, different conventional HMS continue to encounter challenges in their capabilities. Most previous applications are mainly developed to automate management works while providing limited assistance for automated decision-making and forecasting analysis. In other words, clinical professionals often relied on handwritten assessment of patient information, which can lead to delays in diagnosis, inefficient material utilization, and issues in prioritizing patient care. Furthermore, conventional systems often lack advanced predictive attributes required for early detection of patients who may be at strong risk and in need of urgent medical intervention [1].

Recent development in automation of hospital management using AI and machine ML have established critical opportunities for enhancing healthcare discovery and administration. AI-driven technologies are good for analyzing great number of healthcare datasets, discovering complex patterns and providing predictive highlights that enhance evidence-based medical decision-making. ML methods have shown promising frameworks in areas including disease forecasting, patient risk assessment, personalized treatment recommendations, and efficient optimization of healthcare resources [2].

Some of the categories of ML techniques includes the SVM which were used globally based on its recognition for its efficiency in solving classification issues and problem involving complicated and strong-dimensional datasets. SVM recognize optimal decision boundaries by maximizing the margin between different subjects, allowing accurate classification and forecasting of new, unseen data instances. Existing studies have indicated the effectiveness of SVM in healthcare system, especially in areas including disease diagnosis, patient risk prediction, and medical decision assistance [3].

The integration of ML algorithm into hospital administrative applications offers a promising procedure to bridging the gap between routine management intelligent and automation clinical decision assistance [4]. Through the integration of predictive assessments capabilities within healthcare information frameworks, hospitals can improve patient care across early recognition of potential risks while enhancing operational efficiency and resource administrative.

The importance of this research is indicated in its contribution to the growth of field of AI driven healthcare systems. The presented model shows the practical development of ML methods within hospital ecosystems and introduced an effective method for improving healthcare delivery, especially in settings with little resources [5].

## Related Works

Ibewesi & Uzuke, explores a ML based maternal health risk forecasting system developed to improve the early identification of health risks among pregnant women. The research utilized medical and physiological indicators to forecast maternal health outcomes, highlighting the critical automated healthcare systems in reducing maternal mortality rates and assisting clinical caregivers in making correct, updates, and timely decisions [7].

The research utilized logistic regression, SVMs and decision tree methods for healthcare danger assessment. Prior to framework evaluation, the dataset underwent preprocessing and feature extraction and data partitioning including testing and training to promote efficient model development and verifications. The result of the introduced

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frameworks was assessed using metrics like accuracy, precision, recall, and F1-score to test their efficiency and reliability [8].

The outcomes of the findings indicated that the Decision Tree model shows strongest performance, delivering 86.99% of accuracy, 86.40% of precision, 85.70%of recall, and 85.90% of F1-score. The results of the model indicate the ability of ML methods in enhancing healthcare risk prediction and assisting clinical decision-making. Consequently, the implemented framework was especially trained and assessed using maternal healthcare datasets, which may reduce its applicability and generalizability throughout diverse healthcare domains [6].

Ngozi et al., implement an automated healthcare risk prediction system based on assisting SVM frameworks to improve patient risk evaluation and support healthcare professionals in the early recognition of high-risk individuals. The research highlighted the role of forecasting assessment in enhancing clinical decision-making, allowing timely interventions, and reducing potential negative health outcomes. The author proposed utilizing SVM classification methods to analyze patient health records and provide forecasting risk evaluations. The important healthcare properties were analyzed using the SVM framework to categorize patients into various risk levels based on their clinical conditions, medical features, and health indicators [8].

The findings demonstrated that the implemented framework delivered 90.2% of accuracy, 89.1% of precision, 88.7% of recall, and 88.9% of F1-score. The findings show effectiveness of SVM techniques in healthcare risk forecast and its potential to improve the early detection of strong-risk patients. Consequently, the research acknowledged that the use of a commonly small dataset may constrained the framework's generalizability when used to broader and more diverse healthcare populations.

Sharma & Verma, explore a SVM based disease forecasting system focused at improving disease diagnosis and enhancing patient risk evaluation in healthcare settings [9]. The research focused on applying ML methodologies to strengthen clinical decision assistance, promote accurate forecasts, and enhance the overall effectiveness of healthcare service attainment. The study enhanced an SVM classification model using patient medical records and healthcare indicators. The techniques involved training and testing the system utilizing healthcare data and assessing its performance employing standard ML metrics.

The research delivered 91.6% of accuracy, 90.8% of precision, 90.1% of recall, and 90.4% of F1-score. These results highlighted the efficiency of SVM techniques in healthcare forecasting works, showing enhanced classification performance compared to many conventional procedures. Consequently, the study recognized computational complexity as a primary limitation when addressing large-scale healthcare datasets and recommended the examination of hybrid SVM-based mechanisms to improve performance and scalability in future study.

Raj et al. investigated the application of SVM frameworks for casting patient risk levels within healthcare information systems [10]. The research focused to improve healthcare service discovery by utilizing ML methods to generate automated risk evaluations and assist timely, data-driven medical decision-making. The authors developed an SVM-based forecasting framework trained on healthcare data containing patient medical records and health indicators. The framework was assessed employing standard ML performance metrics to confirm its forecasting effectiveness [11].

The research achieved 91.40% of accuracy, 90.50% of precision, 89.20% of recall, and 89.80% of F1-score. These results indicated that, SVM is strongly effective for patient risk classification and healthcare forecasting systems. Consequently, the researchers highlight that the accuracy and high predictive results are critically impacted by the quality of available data and the efficiency of feature selection methods [12].

## Methodology

This chapter proposes the methodology adopted for the development of an HMS leveraging SVM method. The techniques provide a systematic procedure for designing, implementing, and assessing the introduced system to handle the challenges related with conventional hospital administration solutions [13]. The introduced mechanisms involve various key phases, such as system requirement analysis, data acquisition, data preprocessing, system development, model design, implementation, and performance evaluation. Patient healthcare data is analyzed and evaluated utilizing the SVM technique to detect patterns and provide forecast insights for patient risk [14].

### System analysis and design

System analysis and design illustrated in figure 1 is a significant phase in the implementation of the HMS leveraging SVM method. This phase focuses on assessing system requirements, analyzing operational issues, and developing a presented solution that embeds ML capabilities with conventional hospital management functionalities.

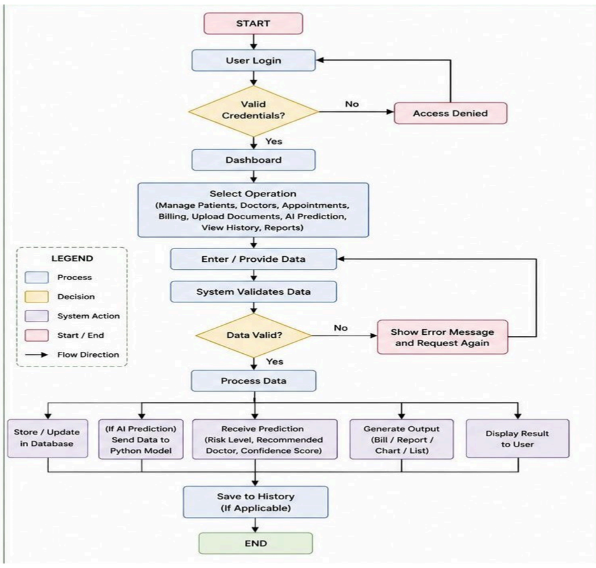


**Figure 1.** System architecture of the proposed hospital management system.

The following steps are the implementation procedures:

The workflow in figure 1 illustrates the methodology of a healthcare management system incorporated with AI-based prediction. The analysis starts when the user logs into the application. The entered profiles are validated, and if they are not correct, access is denied and the user is move to the login page to try again. If the profiles are valid, the user is allowed access to the application dashboard.

In accordance with the dashboard, the user selects the desired activities, including managing patients, administering doctors, scheduling appointments, billing, uploading medical documents, generating AI forecasts, displaying patient history, or establishing reports. After selecting an activity, the user enters or provides the required information related to the profiles.

### Data acquisition

Data for this study were gathered from the University of Ilorin Teaching Hospital (UITH) to support the development and evaluation of the proposed HMS leveraging SVM technique. The data collection focused on major operational areas of the hospital, including doctors, patients, appointments, admissions, treatments, and billing records.

A total of 5,000 hospital records were acquired for the research. The records provided information relating to patient registration and demographic details, appointments, hospital admissions, medical treatments, healthcare providers, and financial transactions. These records were selected because they represent important activities



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involved in the day-to-day management of hospital services and provide important information for implementing an integrated HMS.

The patient data contained important information required for patient identification and clinical management, while the doctor data provided information about healthcare professionals and their respective areas of expertise. Appointment records contained information concerning scheduled consultations and visits, such as appointment dates and status. Admission records provided information about patients admitted to the hospital, like admission and discharge details. Treatment records contained information relating to diagnoses, treatments administered, medications, and treatment outcomes. Billing records provided information concerning hospital services rendered and their corresponding financial charges and payment status.

The application then executes data verification to ensure that all mandatory disciplines are correctly completed and that the entered data is correct. If the validation fails, an error message is flag off, and the user is instructed to correct and resubmit the information required. Once the data passes verifying, the application moves to assess the information.

In the data processing, the application executes different actions relying on the selected operation. It stores or updates records in the database to give current information. If the operation activities involve AI prediction, the important patient data is sent to a Python-based ML model, which assess the data and returns forecasting outputs including the patient's risk level, the suggested specialist or doctor, and a reliable score for the prediction.

In addition, after processing is finish, the application provides the appropriate outcomes, which may consist of bills, reports, charts, or lists, relying on the selected function. The evaluated outcomes, consisting of AI forecasting where applicable, are indicated to the user.

## Support vector machine integration

The gathered dataset was subsequently divided into appropriate subsets for training and testing of the SVM model. The model was developed to identify patterns within the available hospital data and provide predictive or classification support for hospital management activities. The performance of the developed model was evaluated using appropriate classification metrics such as accuracy, precision, recall, and F1-score.

The outcome column is the target variable that the SVM learns to predict (Table 1).

**Table 1.** Extracted datasets after data preprocessing.

| Patient No | Age | Sex | Temp | Heart rate | Glucose | BP | Previous Visit | Diagnosis | Treatment | Outcome |
|---|---|---|---|---|---|---|---|---|---|---|
| P001 | 54 | M | 38.2 | 150/95 | 102 | 185 | 4 | Diabetes | Medication | High risk |
| P002 | 31 | F | 36.8 | 120/78 | 74 | 95 | 1 | Malaria | Medication | Low rsk |
| P003 | 67 | M | 39.1 | 160/100 | 110 | 220 | 6 | Hypertension | Medication | High risk |

The outcome column is the target variable that the SVM learns to predict. Predicting high-risk vs low-risk patients

Consequently, the system saves the finished transaction or forecasting into the patient's history for more reference, confirming that the records are maintained for reporting and decision-making functionalities. The analysis then terminates, finishing one full operational cycle.

This mechanism confirms protect user authentication, correct data verification, effective data evaluation, seamless incorporation of AI-based forecasting, strong database administration, and detail record keeping, consequently enhancing the effectiveness and quality of healthcare management operations.

## Results

The section introduces the design and development of a HMS Leveraging the algorithm called SVM. The proposed model was implemented to analyze and assess to facilitate the operational activities of HMS while using SVM model for predicting patient risk levels [15]. The results demonstrate the system's ability to integrate conventional hospital management functionalities with intelligent ML techniques to support healthcare decision-making.

**Table 2.** Development tools.

| Class | Programming tools |
|---|---|
| Frontend | Html, Css, Bootstrap and JavaScript |
| Backend | PHP programming |
| Database management system | MySQL |
| Machine learning language | Python |
| Machine learning library | Scikit-learn |
| Data processing libraries | Pandas, NumPy |
| Integrated development environment | Visual studio code |
| Local server environment | XAMPP |

## Model performance evaluation

The evaluation performance of the proposed model was assessed using globally adopted ML evaluation metrics to confirm its effectiveness in forecasting patient risk levels.

**Table 3.** Performance evaluation hospital management system.

| Metric | Value (%) |
|---|---|
| Accuracy | 84.42 |
| Precision | 81.25 |
| Recall | 86.11 |
| F1-Score | 83.61 |

### Interpretation of the performance evaluation hospital management system

The evaluation results in table 3 and figure 2 show that the implemented HMS, using SVM method, delivered effective performance in patient risk prediction. The proposed framework attained 84.42% of accuracy, showing that it correctly classified approximately 4,221out of every 5, 000 patient cases. This finding



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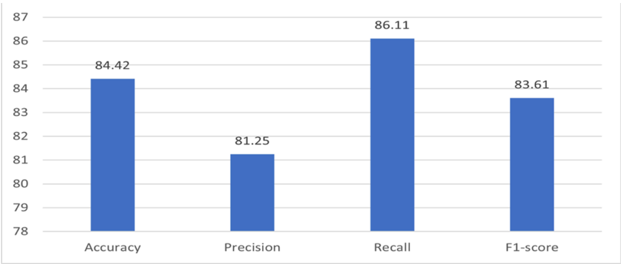


**Figure 2.** Performance evaluation hospital management system.

suggests that the SVM algorithm successfully trained the underlying patterns within the healthcare dataset and was able to provide reliable and consistent predictions.

The model attained a precision of 81.25%, indicating that a large proportion of patients predicted to belong to a particular risk category were accurately classified. In healthcare applications, a high precision value is desirable because it reduces false-positive predictions, consequently, minimizing unimportant clinical procedures, resource utilization, and related healthcare costs. Furthermore, the recall of 86.11% shows the model's high ability to recognize patients who genuinely belong to the high-risk classes. This strong recall is particularly valuable in clinical settings, where early detection of at-risk patients allows timely clinical intervention and assists to minimize the likelihood of adverse health results.

In addition, the model delivered an F1-score of 83.61%, demonstrating well-balanced relationship between precision and recall. Generally, these assessment metrics indicates that the SVM model is responsible for providing reliable patient risk classification and can serve as an efficient decision assistance device within hospital administration systems.

## Confusion matrix analysis

The evaluation of the classification performance of the proposed model, a confusion matrix was provided by comparing the model's predicted classifications with the actual patient risk categories. The confusion matrix explains a comprehensive breakdown of correctly and incorrectly classified instances, offering valuable result into the framework's ability to differentiate between various patient risk levels and detect areas where misclassifications occur.

**Table 4.** Confusion matrix.

| Actual / Predicted | Predicted low risk | Predicted high risk |
|---|---|---|
| Low risk | 85 | 10 |
| High risk | 14 | 45 |

The confusion matrix in table 4 shows that the model accurately classified 85 low-risk patients and 45 high-risk patients. Consequently, ten (10) low-risk datasets were not predicted correctly as strong risk (false positives), while fourteen (14) high-risk datasets were not classified correctly as low risk (false negatives). Consequently, some misclassifications occurred, the overall distribution of correct predictions indicates that the model performs efficiently in differentiating between low-risk and high-risk datasets.

## Discussion

The performance evaluation indicates that the implemented HMS integrated with the SVM model achieved satisfactory performance in patient risk forecasting. The framework delivered an accuracy of 84.42%, showing that approximately 84 out of every 100 patient cases were correctly classified. This finding recommends that the SVM techniques efficiently learned hidden patterns within the healthcare dataset and generated strong predictive outcomes.

The precision result of 81.25% indicates that a substantial proportion of patients predicted to belong to one risk class were correctly recognized. In healthcare settings, maintaining strong precision is important because it minimizes false-positive predictions that could lead in unimportant clinical interventions and increased healthcare costs. Similarly, the recall score of 86.11% indicates the proposed model's ability to successfully recognize majority of actual high-risk patients within the dataset. The high recall value is particularly necessary because overlooking high-risk victims might result to slow treatment and negative health outcomes.

In addition, the model attained an F1-score of 83.61%, demonstrating a balance between precision and recall. F1-score demonstrates that the framework maintained consistent forecasting performance without excessively prioritizing one evaluation metric at the expense of another. The injection of these performance indicators shows that the SVM model is good for assisting in automating decision-making within hospital ecosystems.

## Conclusion

This research introduced the implementation of a HMS utilizing SVM Technique focused on injecting conventional hospital management functionalities with automated ML capabilities. The implemented system was designed to handle limitations related with conventional healthcare administration systems, especially challenges in patient risk assessment, decision assistance, and efficient utilization of healthcare data. By integrating the SVM technique, the system provides forecasting capabilities that support healthcare professionals in detecting patient risk levels and assisting timely medical decision-making.

The evaluation results indicated that the implemented SVM model delivered satisfactory forecasting capability, achieving 84.42% of accuracy, 81.25% of precision, 86.11% of recall, and 83.61% of F1-score. The accuracy results shows that the framework was able to correctly evaluate a critical proportion of patient data, while the precision and recall values declare its efficiency in detecting patients within their appropriate risk categories. The strong recall score indicates the model's ability to recognize most strong-risk patients, which is particularly necessary in healthcare ecosystems where early recognition can assist timely intervention and enhanced patient outcomes. Despite the model attained satisfactory forecasting performance, its efficiency could be in addition improved across the injection of big and more diverse healthcare datasets, enhanced feature engineering techniques, hyperparameter optimization, and comparative assessment with other ML methods to deliver even greater forecasting accuracy and generalizability.

## Limitations

Despite the successful implementation of the Hospital Management System leveraging SVM Technique, certain challenges were noticed that may influence the system's performance, scalability, and applicability in broader healthcare ecosystems.

### Limited dataset availability

The performance of the SVM model is strongly relied on the quality, quantity, and diversity of the healthcare dataset used for training and testing. The dataset utilized in this research may not fully represent the variations in patient conditions through various hospitals and populations, which may limit the model's ability to generalize effectively to other healthcare ecosystems.

## Recommendations

The development and assessment of the HMS using SVM Technique, the following recommendations are presented to improve the system's performance, scalability, and practical application in healthcare ecosystems:

### Utilization of larger and diverse healthcare datasets

Development should inject larger and more diverse healthcare datasets acquired from multiple healthcare institutions. This will



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enhance the ability of the SVM model to learn various patient patterns and improve its generalization capability through various healthcare populations.

## Contribution to Knowledge

This project contributes to the field of healthcare information systems by demonstrating a practical approach to integrating ML into HMS. It highlights how AI can be used not only for automation but also for intelligent decision support in clinical environments.

The system serves as a model for future research and development in AI-driven healthcare applications, particularly in resource-constrained environments where efficient and intelligent systems are highly needed.

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