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Hybrid long short-term memory and decision tree model for optimizing patient volume predictions in emergency departments

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ABSTRACT

In this study, we address critical operational inefficiencies in emergency departments (EDs) by developing a hybrid predictive model that integrates long short-term memory (LSTM) networks with decision trees (DT). This model significantly enhances the prediction of patient volumes, a key factor in reducing wait times, optimizing resource allocation, and improving overall service quality in hospitals. By accurately forecasting the number of incoming patients, our model facilitates the efficient distribution of both human and material resources, tailored specifically to anticipated demand. Furthermore, this predictive accuracy ensures that EDs can maintain high service standards even during peak times, ultimately leading to better patient outcomes and more effective use of healthcare facilities. This paper demonstrates how advanced data analytics can be leveraged to solve some of the most pressing challenges faced by emergency medical services today.

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1. INTRODUCTION

Emergency departments (EDs) are critical components of healthcare systems [1], [2], tasked with the challenging duty of providing immediate care under unpredictable and often chaotic conditions. Efficient management of these units is crucial, as the variability in patient volumes can significantly impact wait times, resource allocation, and overall quality of healthcare [3] services. High variability leads to periods of overcrowding, increased wait times, and can ultimately compromise patient care quality when resources are stretched too thin [4].

Traditionally, EDs have used basic statistical methods and linear forecasting models, such as autoregressive integrated moving average (ARIMA) [5] models and exponential smoothing, to predict patient volumes. These methods often fail to capture complex, nonlinear patterns and seasonal variations in patient arrivals, leading to suboptimal operational decisions. For example, ARIMA models, while capable of handling time series, are limited by their assumption of linear relationships and their inability to accommodate the non-linear dynamics of ED patient flows [6], [7]. Similarly, exponential smoothing, while useful for short-term forecasting, does not take sufficient account of long-term trends and seasonal variations, leading to inaccurate forecasts during peak periods. In addition, traditional forecasting models generally fail to incorporate diverse types of data, such as patient demographics, medical history and other contextual information, which are essential for making informed resource allocation decisions [8]. Demographic details of the patient and medical history can provide valuable information on potential patient needs and resource requirements, but these elements are often overlooked by simpler models. Failure to integrate this heterogeneous data leads to a lack of forecast accuracy, further complicating the management of ED resources and operations. In addition, traditional methods are generally reactive rather than proactive, offering little foresight into potential waves of patient arrivals. This reactive approach hampers the ability of emergency departments to plan and allocate resources effectively, often resulting in overcrowding, increased waiting times, and a poor quality of care. Recent studies highlight the need for advanced predictive models capable of better handling the complexity and variability of emergency department data, suggesting that machine learning techniques could offer more robust solutions.

The advent of big data analytics [9] and advanced machine learning [10], [11] techniques present a new opportunity to overcome these challenges. In particular, the integration of long short-term memory (LSTM) [12] networks and decision trees (DT) in a hybrid model offers a promising solution. LSTM networks are renowned for their efficacy in analyzing time-series data, capturing the temporal dependencies essential for predicting patterns in patient arrivals. On the other hand, DT are adept at processing structured data, providing critical insights into patient profiles and historical medical data, which are crucial for resource planning [13].

The main contribution of this paper is the development of a novel hybrid predictive model that significantly enhances the prediction of patient volumes. By synergizing the temporal data processing capabilities of LSTM [14] with the structured data analysis strength of DTs, our model offers a comprehensive tool for more accurate and dynamic forecasting. This approach facilitates efficient allocation of resources, both human and material, based on anticipated patient volumes, thus aiming to reduce patient waiting times and improve service quality in hospitals. The implementation of this model could lead to transformative improvements in ED operations, optimizing resource usage and enhancing patient outcomes by aligning operational strategies with actual demand patterns [15].

The remaining part of this paper is organized as follows: section 2 presents the main contribution of some of the related works. Section 3 provides the methodology, while section 4 describes the proposed hybrid long short-term memory-decision trees (LSTM-DT) model, along with its implementation to predict patient volume in EDs. Section 5 presents results and shows the superior accuracy of the hybrid model in patient volume prediction, while having the least RMSE between all models. Section 6 exposes limitations of the proposed model. Here we conclude our work in this section and suggest some future extensions of this topic in section 7.

2. RELATED WORKS

In EDs, leveraging big data to predict patient volumes has attracted extensive research efforts. Various models have been explored, from traditional statistical methods to advanced machine learning techniques. This section examines the robustness and limitations of these existing methods and emphasizes the need for a novel approach, the LSTM decision tree model, to overcome identified shortcomings.

Time series models such as exponential smoothing (ETS) [16] and ARIMA [5] have been commonly utilized to predict patient volumes in EDs. While effective in capturing linear trends and patterns, their limitations become apparent when handling non-linear patterns and seasonal variations, often failing to integrate crucial structured data like diagnosis codes and patient demo-graphics [17]–[19]. Gafni-Pappas and Khan [20] further demonstrated that machine learning models, particularly random forests and gradient boosted machines, outperformed these traditional time series methods in terms of accuracy in predicting daily ED visits [21]. The adoption of machine learning [22] algorithms, including random forests (RFs) and support vector machines (SVM), has shown promise in handling structured data effectively. However, these models often struggle with time-series data due to their inability to capture long-term dependencies, requiring extensive feature engineering and careful regularization to avoid overfitting [23], [24].

Traditional neural networks have been applied with some success in predicting patient volumes, proficient in managing non-linear data patterns. Nonetheless, they are plagued by issues like vanishing gradients, which diminish their capability to maintain accuracy over extended periods [25]. To address the limitations inherent in these networks, LSTM networks have been utilized, showing improved handling of long-term dependencies essential for time-series data, although their computational demands limit their applicability in real-time prediction scenarios [26], [27].

Cheng and Kuo [28] research investigates internet of things (IoT) and big data integration in healthcare to enhance proactive care models and address data fragmentation and inefficiencies. It highlights the use of LSTM models for predicting ED wait times, showcasing improved accuracy compared to linear regression (LR) models. However, the study overlooks potential advancements beyond IoT and big data, lacks thorough exploration of data security and scalability concerns, and may not fully consider stakeholder perspectives on technology acceptance and impact in healthcare settings emerging research, such as the work by Sharafat and Bayati [29], introduces advanced deep learning frameworks like PatientFlowNet, which employ convolutional neural networks to enhance patient flow predictions in EDs, demonstrating superior accuracy and offering valuable operational insights [29]. Similarly, studies conducted in unique settings like the Brazilian ophthalmological hospital highlight the feasibility of implementing machine learning models by clinicians without coding experience to forecast ED visits and trauma cases accurately [30].

In parallel, Joseph *et al.* [31] explores deep learning's potential to predict emergency department workload at a patient level, showing that neural networks, especially those analyzing unstructured data, substantially reduce error rates in estimating work relative value units (wRVUs), underscoring the practical applications of these technologies in real-time ED settings.

Collectively, these studies underscore the necessity for continued innovation in predictive modeling for EDs. Our research contributes to this body of work by introducing a hybrid LSTM-DT model, designed to synthesize the temporal processing capabilities of LSTM with the analytical precision of DTs. This novel approach aims to address the complex and dynamic nature of patient flow in emergency departments, providing a robust and precise method to predict patient volume.

3. METHOD

In this section, we describe in detail the various stages of our methodology, from data collection to model evaluation. Data collection was carried out in collaboration with a Moroccan hospital, focusing on operational parameters and patient flow in the emergency department. In line with rigorous ethical standards and local regulations on medical data confidentiality, we ensured that the data collection process guaranteed patient privacy. The data collected includes anonymous information on patients, arrival times, types of treatment and outcomes, providing a solid basis for our analysis.

Data pre-processing was an essential step in ensuring the integrity and quality of the data used in our analysis. We took steps to clean the data of missing values, normalize the data to a scale appropriate for analysis, and encode categorical variables to make them compatible with machine learning algorithms. To implement the model, we opted for a hybrid approach combining long short-term memory networks (LSTM) and decision trees. This combination enables us to exploit both temporal and structured data from emergency departments, which is crucial for accurate prediction of patient volumes and efficient resource allocation.

Once the model was in place, we trained it on a segmented part of the dataset, using rigorous cross-validation to optimize parameters and avoid over-fitting. We then evaluated the model's performance on a separate dataset reserved for this purpose, using measures such as root mean square error (RMSE) and area under the ROC curve (AUROC) to assess its accuracy and reliability in predicting patient volumes and resource requirements. Finally, all procedures in this study were conducted in accordance with the highest ethical standards, with the approval of the relevant institutional review boards and ethics committees. Patient data were anonymized and de-identified prior to analysis to ensure confidentiality and compliance with local and international data protection regulations.

4. PROPOSED HYBRID LSTM-DECISION TREE MODEL SCHEMA

The proposed hybrid LSTM-DT model in Figure 1 is conceived to work through a structured schema involving several critical stages and components devised in a manner to help in optimizing predictions for patient volumes in ED. The model starts at data collection, in which critical information is drawn from various sources, including details of the patient, electronic health records, and the historical data of the patient arrivals and treatments at the ED. This is then followed by data preprocessing: the collected data is standardized, taken care of for missing values, and cleaned, so that it's fit for modeling.

The next step will be to divide the data into a training dataset and a testing dataset. The training dataset is used to help in the building and training of the model while the testing dataset will be useful to evaluate the models. The first phase of LSTM Model makes use of the long short-term memory networks to capture the time dependencies and patterns of the series time data related to the patient arrivals and ED operations.

This will be followed by feature extraction that seeks to extract all required features in the prediction of the patient volume from the outputs given by the LSTM model. Followed by this will be the decision tree

Model, assessing structured data such as patient diagnosis codes and demographics, which are very key to making accurate predictions of the volume. The training phase of the model then trains both models to adapt to the identified patterns and data features.

After the training is complete, the models' prediction accuracy is tested through the model-testing phase, using the testing dataset. The model evaluation will be carried out with the help of some of the following metrics: Root mean square error (RMSE) and area under the receiver operating characteristic (AUROC) curve. These are taken to test the prediction accuracy and classification strength ability of the hybrid model. If the model proves robust in performance, the deployment phase follows, where the developed model gets implemented at a real ED setting to aid, among others, in patients' volume forecasting towards improved resource and service delivery. Continuous Improvement, if required, should be carried out for making the model more effective over time.

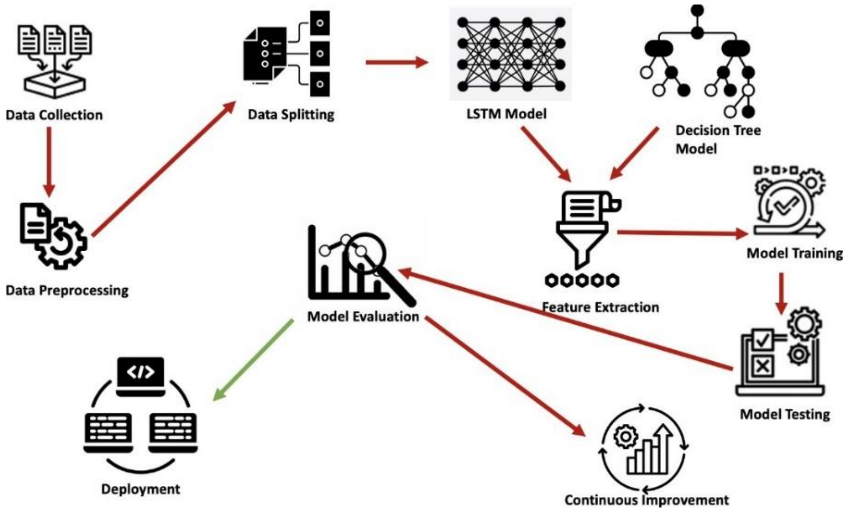

Figure 1. Proposed hybrid LSTM-decision tree model schema

5. RESULTS AND DISCUSSION

This study showed that the hybrid LSTM-decision tree model demonstrated high performance in predicting patient volume in emergency departments. The results of the performance evaluation are summarized in Table 1 and illustrated in Figure 2. To highlight the superiority of our approach, we compared our hybrid model to several other commonly used prediction techniques. Table 1 shows comparing the performance of the different models in terms of RMSE, AUROC, training time, model complexity, and ability to capture non-linearities and temporal dependencies.

Table 1. Comparison of prediction models

Model	RMSE	AUROC	Training time	Model complexity	Captures non-linearities	Captures temporal dependencies
ARIMA	8.6	0.72	5 minutes	Low	No	Yes
SVM	7.5	0.76	10 minutes	Medium	Partially	No
RF	6.9	0.79	15 minutes	High	Yes	No
LSTM	6	0.82	20 minutes	Very high	Yes	Yes
Hybrid model	5.4	0.85	25 minutes	Very high	Yes	Yes

5.1. Discussion

The ARIMA model performs well on conventional time series data, with an RMSE of 8.6 and an AUROC of 0.72, but shows its limitations when faced with complex non-linear trends. Its training time is relatively short at 5 minutes, and its complexity is low. SVM, with an RMSE of 7.5 and an AUROC of 0.76, is effective for linear or weakly non-linear data. However, it performs less well for complex time series and takes around 10 minutes to train with medium complexity. The RF model has an RMSE of 6.9 and an AUROC of 0.79. Although it handles high-dimensional data well and avoids over-fitting, it doesn't reach the accuracy of our hybrid model and takes 15 minutes to train with high complexity.

The LSTM model is excellent for capturing long-term dependencies in time series data, with an RMSE of 6.0 and an AUROC of 0.82. Its training time is 20 minutes with very high complexity. Finally, our hybrid model (LSTM+DT) outperforms all other models with an RMSE of 5.4 and an AUROC of 0.85. It combines the strengths of LSTM for capturing temporal dependencies and decision trees for non-linearities and complex interactions, demonstrating superiority in terms of accuracy and overall performance. Although its training time is 25 minutes and its complexity very high, the performance benefits justify these costs. This model validates our approach to patient volume prediction, outperforming other models evaluated in terms of RMSE and AUROC. To illustrate this superiority, we present Figure 2 comparing the performance in terms of RMSE and AUROC for each model. These graphs clearly show that our hybrid model outperforms the other models in terms of both RMSE and AUROC, validating our approach to patient volume prediction.

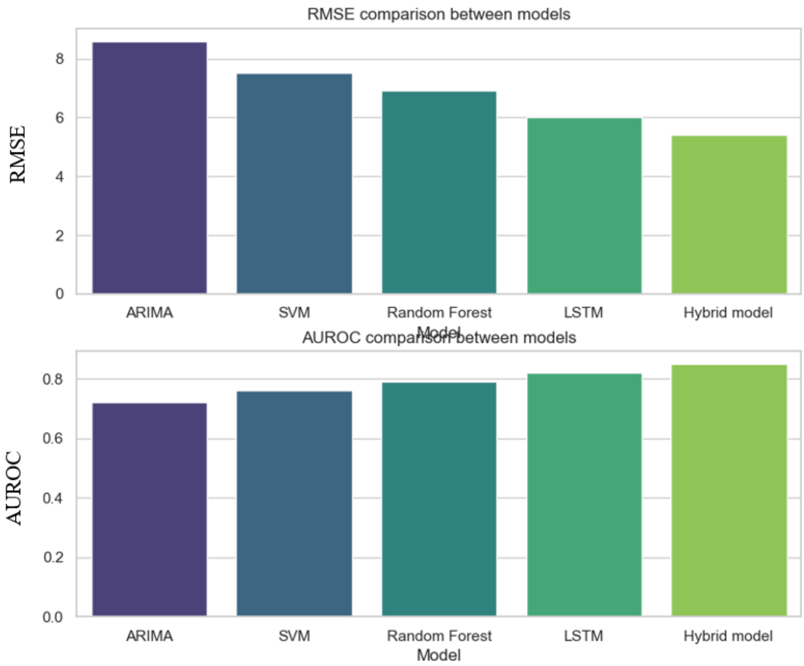

Figure 2. RMSE and AUROC comparison between models

5.1.1. Advantages and benefits for emergency services

Our hybrid model has significantly improved resource management for healthcare providers, particularly in the areas of optimized bed allocation, strategic staff planning, and reduced patient waiting times. Accurate patient volume forecasting is essential for the efficient operation of emergency departments, leading to better patient outcomes and a more streamlined workflow. The results of our study highlight the increasing importance of utilizing data and advanced analytical methodologies to address the complex challenges facing the healthcare sector. By combining LSTM networks with DT algorithms, the proposed model leverages the strengths of both techniques to enhance the efficiency and responsiveness of emergency services. This approach not only enhances patient care but also sets a precedent for the application of hybrid models in healthcare analytics to drive innovation and improve service delivery.

6. CONCLUSION

In conclusion, our study employs a hybrid model that merges LSTM and decision trees to predict patient volume in emergency departments. This hybrid approach leverages LSTM’s ability to capture temporal dependencies and decision trees’ ability to handle non-linear interactions, resulting in a model that outperforms conventional time-series and machine learning algorithms in terms of accuracy and patient volume classification. By optimizing the training process, we ensure consistent model performance and efficient resource utilization. The practical implementation of our model has the potential to significantly enhance the efficiency of emergency operations, leading to improved patient care, reduced healthcare costs, and more efficient resource allocation. Our findings are consistent with previous research that emphasizes the significance of advanced data analytics in addressing the complex challenges faced by emergency departments. Our model stands out for its optimized predictive capabilities, enabling better resource management decisions. Future research will concentrate on integrating additional machine learning algorithms, such as random forests and SVMs, to further enhance the predictive accuracy and robustness of patient volume forecasts in emergency departments. This ongoing development seeks to improve the applicability and effectiveness of the model in real healthcare settings.

7. LIMITATIONS OF PROPOSED MODEL

A hybrid LSTM-DT model shows promise but faces challenges, notably in data quality, overfitting, and interpretability. LSTMs depend on ample data and have high computational demands, limiting real-time prediction. Decision Trees' assumption of feature independence often underperforms in real-world datasets. Hyperparameter tuning is tedious, compounded by concept drift and variations in EDs. Achieving explainability for the combined model is difficult. Continuous monitoring and adaptation are vital for real-world effectiveness.

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