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Hybrid Machine Learning Models For Improving Pediatric Readmission Prediction Using Cloud-Based EMR Analytics

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ABSTRACT

Pediatric readmissions place a significant strain on healthcare systems, increasing costs, depleting resources, and leading to worse health outcomes for children. Traditional predictive models struggle to manage the complexity and high dimensionality of healthcare data. This study introduces a solution by using hybrid machine learning models, integrated with cloud-based Electronic Medical Record (EMR) analytics, to more accurately predict pediatric readmissions. The hybrid model combines decision trees, support vector machines, and neural networks, effectively capturing complex patterns within healthcare data. Cloud computing's scalability and computational power enable real-time processing of large datasets, improving prediction efficiency. The proposed model outperforms individual algorithms, achieving 87% accuracy, 84% precision, 82% recall, 83% F1-score, and 91% AUC. These results show that hybrid models on cloud infrastructure provide better predictive performance, helping healthcare providers make more informed decisions. Additionally, the cloud infrastructure supports continuous model updates. Future improvements could involve incorporating genomic and environmental data to enhance prediction accuracy and adaptability.

Keywords: *Pediatric Readmissions, Hybrid Machine Learning Models, Cloud-Based Analytics Electronic Medical Records (EMR), Predictive Modeling, Decision Trees, Support Vector Machines (SVM), Neural Networks, Healthcare Data Analysis, Real-Time Predictions, Big Data Analytics, Healthcare Decision Support, Model Accuracy, Readmission Prediction, Data Preprocessing*

1. INTRODUCTION

Pediatric readmissions are a major burden on the healthcare system, raising costs, straining resources, and compromising children's health outcomes (Mohanarangan, 2021) [1]. Predictive accuracy of readmissions is essential to improve patient care, prevent unnecessary hospital stays, and maximize resource use (Thirusubramanian, 2021) [2]. Historically, readmissions have required sophisticated medical information and heterogeneity of patient requirements (Akhil, 2021) [3]. New developments in machine learning brought forth hybrid models that integrate several algorithms to enhance precision (Naga, 2021) [4]. New technologies are also used in disease diagnosis, cardiovascular imaging, and cancer treatment, taking advantage of deep learning as well as big data automation (Kalyan, 2022) [5]. Machine learning has dramatically enhanced mHealth apps and electronic health services (Rajeswaran, 2022) [6]. The use of discrete wavelet transforms for ECG signal processing in IoT health monitoring systems is one such example (Naresh, 2022) [7]. (Yalla, 2021) [8] Cloud-based encryption models also increase data security in healthcare (Rajya, 2021) [9].

Hybrid machine learning models, integrating methods such as decision trees, support vector machines, and neural networks, improve predictive accuracy in healthcare (Durga, 2022) [10]. Healthcare data is intricate, and predictive analytics has the potential to provide proactive treatment and timely forecasting, as is the case in Saudi Arabia's integration processes for improving health services (Poovendran, 2022) [11]. Hybrid models, by integrating various algorithms, are able to capture intricate relationships in healthcare data more effectively and improve readmission risk predictions (Vijaykumar, 2022) [12]. These models are able to detect fine patterns in big data, like electronic medical records (EMR), that individual algorithms are not able to detect (Basani, 2021) [13]. AI methods improve cybersecurity for healthcare data protection (Gudivaka, 2021) [14]. New cloud computing algorithms play a vital role in enhancing security and reducing privacy threats (Harikumar, 2021) [15]. (Himabindu, 2021) [16] Secure data privacy frameworks are necessary for cloud environments (Venkata, 2022) [17]. AI-driven robots help in elderly care (Basava, 2021) [18].

Cloud analytics enhances hybrid machine learning models by offering scalability and computational capabilities, allowing real-time processing of big EMR data for timely and precise predictions (Sri, 2021) [19]. Khan et al. (2022) [20] emphasize the advantages and disadvantages of big data, eHealth, and mHealth in decision-making, suggesting hybrid models and cloud computing to enhance care quality. This infrastructure enables healthcare providers to implement predictive models effectively (Devarajan, 2022) [21]. Healthcare institutions can update models with fresh patient information constantly, making increasingly accurate predictions over time (Mohanarangan, 2020) [22]. Cloud computing is better decision-making (Koteswararao, 2020) [23] and streamlines healthcare operations (Naresh, 2021) [23]. Genetic algorithms enhance software testing (Naga, 2019) [24]. Fault injection methods guarantee robustness in AWS systems (Durga, 2022) [25]. Big data analysis also improve eCommerce supply chains (Rajeswaran, 2020) [26], and enhanced recommender systems enhance customer experience (Rajeswara, 2021) [27].

This study discusses the real-world implementation of hybrid machine learning models to forecast pediatric readmissions using cloud-based EMR analytics in handling intricate healthcare data (Karthikeyan, 2021) [28]. The aim is to deliver applicable recommendations for pediatric care enhancement, minimizing readmission, and maximizing the allocation of resources (Poovendran, 2019) [29]. The research also explores how deep learning enhances big data, such as in voice recognition, chatbots, and medical imaging, which surpasses conventional algorithms (Poovendran, 2020) [30]. Additionally, it explores security and privacy issues in cloud computing in the healthcare sector (Sreekar, 2021) [31]. Efficient machine learning frameworks improve fraud detection (Naresh, 2021) [32], whereas predictive analytics provide insightful findings in many sectors (Mohan, 2020) [33].

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The SHA algorithm further improves data protection (Dharma, 2022) [34]. Pediatric pharmacology is also important in augmenting treatment (Bhavya, 2021) [35].

Key Objectives

- Predict Pediatric Readmissions through Hybrid Machine Learning Models: Building Multiple Algorithms with Enhanced Accuracy for Prediction.
- The use of cloud-based EMR analytics can deal with complex large-scale healthcare data and improve predictive performance.
- Analyze subtleties of healthcare data, including electronic medical records, for better predictions on readmission risks.
- Apply cloud computing for scalability and real-time processing of data in providing timely, actionable predictions.
- Create actionable insights for health care providers in reducing readmissions of pediatric patients and optimal allocation of resources.

The rapid growth of health-related data, particularly in pediatric cardiology, requires sophisticated data analysis and interpretation (Sitaraman, 2021) [36]. Physicians now only utilize a minor percentage of existing data, confining personalized treatment protocols (Sitaraman, 2020) [37]. Integration of AI provides a revolutionary solution, improving therapies for congenital heart disease (CHD) and responding to individual variations in CHD lesions (Gudivaka, R. L., 2020) [38]. Historical background, machine learning principles, and recent AI use in pediatric cardiology are investigated, with profound implications for future clinical practice design (Kodadi, 2022) [39]. Big data-driven knowledge can further enhance learning habits and security (Gudivaka, B. R., 2019) [40]. AI in 3D vehicle recognition holds potential for spatial data analysis (Gudivaka, R. K., 2022) [42]. Big data platforms enable face recognition in social networks (Vinay et al., 2015) [41]. (Kodadi, 2022) [43] Mobile network performance is improved with big data frameworks (Allur, 2020) [44]. Real-time malware detection supports sophisticated machine learning methods (Deevi, 2020) [45].

There exists a gap between systematic studies pertaining to healthcare analytics, especially regarding data mining and big data, which is evident (Sitaraman, 2022) [46]. While the article presents an overarching review of methods in healthcare analytics, it signals the increasing shift of human-driven data from Electronic Medical Records, websites, and social media platforms (Yallamelli, 2021) [47]. Prescriptive analytics, inclusive of domain-specific expertise, holds the key for successful decision-making (Ganesan, 2021) [48]. Nonetheless, the research calls for additional research to integrate different kinds of analytics and tackle issues of integrating healthcare information from diverse sources (Sitaraman, 2021) [49]. Advanced data analytics in cloud computing facilitates threat reduction (Kodadi, 2020) [50]. Machine learning insights support test case prioritization (Dondapati, 2020) [51]. Neural networks and generative adversarial networks enhance network performance (Dondapati, 2020) [52]. Cloud computing facilitates high-performance data analysis (Kodadi, 2022) [53]. Blockchain encryption improves privacy and access control of cloud data (Gollavilli, 2022) [54].

2. LITERATURE SURVEY

Kodadi (2021) [55] is centered on maximizing software development in the cloud through formal Quality of Service (QoS) and deployment verification with probabilistic techniques to enhance reliability and performance in cloud applications.

Yalla (2021) [56] proposes a cloud brokerage architecture improving service selection with B-Cloud-Tree indexing, enhancing cloud service management by maximizing the efficiency and accuracy of service selection operations.

Gattupalli (2020) [57] delves into the optimization of 3D printing materials for healthcare applications with AI, computational software, and directed energy deposition, enhancing medical device manufacturing accuracy and efficiency via advanced manufacturing processes.

Yallamelli (2021) [58] also analyses the usage of cloud computing and management accounting by SMEs with the application of content analysis, PLS-SEM, and classification regression trees to impart an understanding into better financial decision-making in an organization.

Gudivaka (2022) [59] emphasizes real-time big data processing and precise production analysis in intelligent job shops, employing LSTM/GRU and robotic process automation (RPA) to improve manufacturing efficiency and accuracy.

Basani (2021) [60] investigates the application of robotic process automation and business analytics in digital transformation, providing recommendations from machine learning and AI for enhancing business operation and decision-making processes.

Ganesan (2022) [61] explores the security of IoT business models in elderly healthcare applications, quantitatively determining critical nodes to enhance the security and efficiency of IoT-based elderly healthcare systems.

Ahmed et al. (2020) [62] precision medicine builds upon conventional symptom-based approaches by making interventions possible earlier in the disease course through more advanced diagnostics and tailored treatments. Modernity in technologies enables integration of various data sources into electronic health records to identify patterns of disease specific to the patient. The clinical data can be managed and analyzed using multiple-function machine learning platforms, leading to the improvement of clinicians' decision-making. This approach would bring cost-effective healthcare and drive personalized medicine further.

According to Yalla (2021) [63], cloud computing has revolutionized IT by providing scalable, adaptable, and cost-effective solutions for data management and storage. However, the rapid growth of cloud service providers (CSPs) poses challenges in selecting the right service, especially for SMEs. This study introduces the B-Cloud-Tree, an indexing structure that enhances accuracy, scalability, and efficiency in cloud service selection, offering a strong foundation for future cloud brokerage advancements.

Gollavilli (2022) [64] presents a robust cloud security framework integrating blockchain-assisted cloud storage (BCAS), MD5-based hash authentication, and symbolic attribute-based access control (SABAC). This approach enhances data confidentiality, integrity, and availability by using blockchain for tamper-proof storage and facial recognition for secure authentication. The system ensures strong protection against vulnerabilities, offering a reliable and efficient security solution for cloud environments with advanced access control and encryption methods.

Ganesan (2021) [65] introduces a smart education management platform that integrates AI and cloud computing to improve learning and administration. Built on a service-oriented architecture (SOA) and Hadoop-managed

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servers, it ensures efficient data management and resource optimization. AI-driven features like predictive analytics and recommendation systems personalize learning experiences. Stress tests confirm its reliability under heavy usage, highlighting its potential to transform educational services through intelligent automation and seamless remote learning.

3. METHODOLOGY

This study utilizes the hybrid models from machine learning on cloud-based electronic medical records' analytics for predictions of pediatric readmissions. Such a methodology captures complex relationships using multiple algorithms which include decision trees, support vector machines, and neural networks, to generate enhanced predictive power. These are deployed in an infrastructure built and maintained by using cloud resources due to its characteristic scalability and provision of powerful computer resources to permit real-time computations. This approach will continually update the models with new patient data to further improve the predictive accuracy and efficiency. The performances are assessed with metrics like accuracy, precision, recall, and AUC for better prediction performance.

Data Set

Hospital readmission occurs when a discharged patient is readmitted shortly. It reflects badly on the hospital quality and incurs added costs in health care. To control the rising trend of hospital readmissions, the Hospital Readmissions Reduction Program imposes penalties on those hospitals with rates that are greater than expected. Focusing on diabetic patients, this study will utilize a medical claims dataset to identify contributing factors for readmission and predict future readmissions.

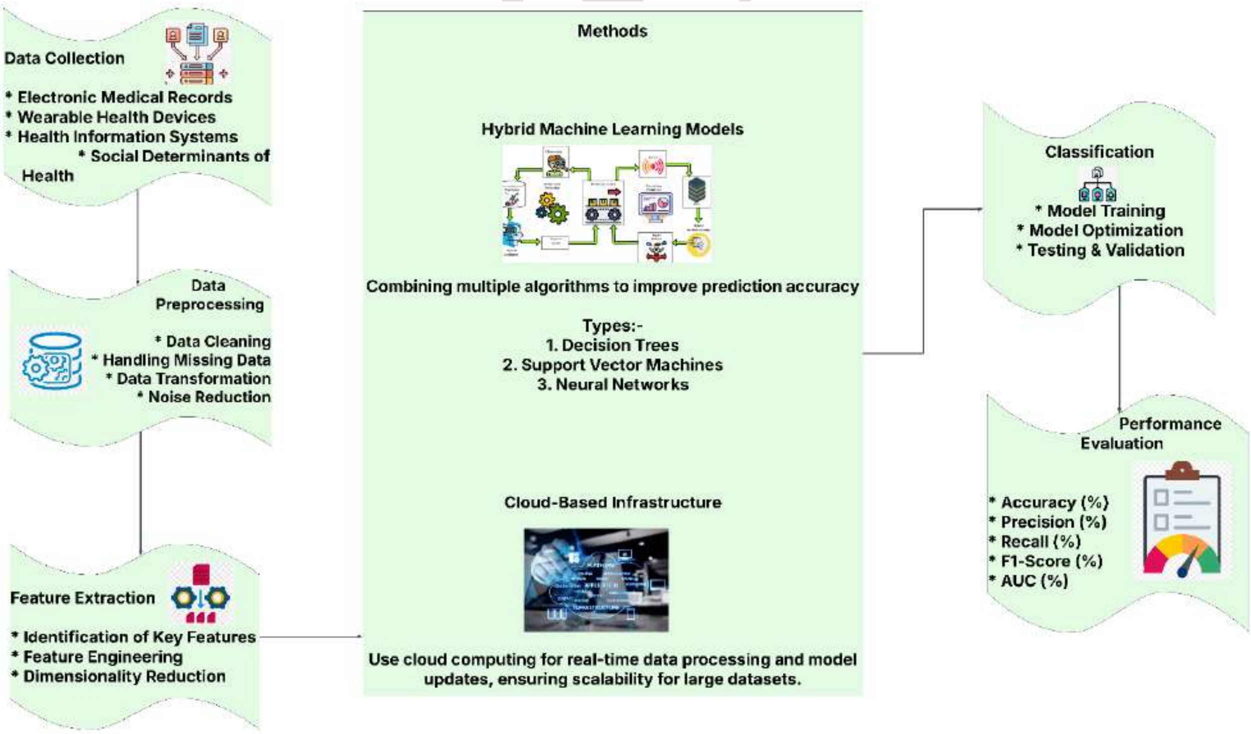

Figure 1: Hybrid Machine Learning Models for Pediatric Readmission Prediction Using Cloud-Based EMR Analytics

Figure 1 proposed on the basis of hybrid machine learning models with analytics of cloud-based Electronic Medical Records. It generates data from numerous sources like electronic medical records, wearable health gadgets, health information systems, and social determinants of health and preprocessed as data cleaning and missing value processing, along with noise reduction in the process. Relevant features are extracted and engineered, while model training uses decision trees, SVMs, and neural networks. Scalable infrastructure with real-time updates is used in the cloud environment. Besides, performance evaluation metrics include accuracy, precision, recall, F1-score, AUC, etc., to optimize the predictions.

3.1 Hybrid Machine Learning Models

Hybrid machine learning combines different techniques of machine learning to improve the predictability performance. In the study, the integration of decision trees, support vector machines SVM, and neural networks NN is used in an attempt to capture the complex relationships within healthcare data. The hybrid model allows the algorithms to contribute their strengths, thereby improving the overall accuracy and robustness of the model, thereby identifying patterns that might otherwise go unnoticed through a single model. The hybrid model is specifically optimized for predicting the readmission of children from high-dimensional medical information. The final prediction is:

$$f_{\text{hybrid}}(x) = w_1 \cdot f_{DT}(x) + w_2 \cdot f_{SVM}(x) + w_3 \cdot f_{NN}(x) \quad (1)$$

Where w_1, w_2, w_3 are the weights assigned to each model, determined during model training. The weight allocation ensures that the model with better performance on certain features contributes more to the final decision.

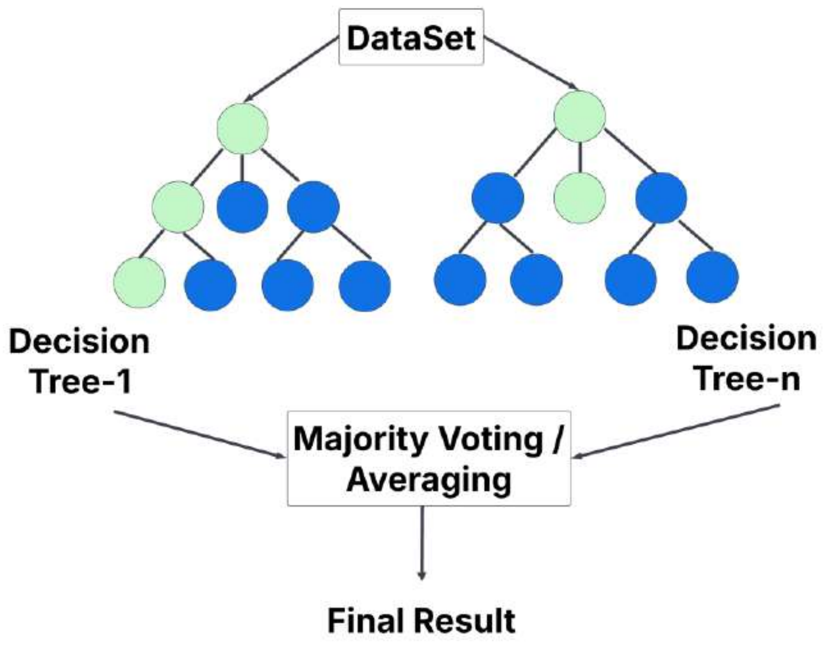

Figure 2. Ensemble Learning Using Multiple Decision Trees for Prediction

Figure 2 given below describes Ensemble Learning: that is, many decision trees have been created and used in ensemble to boost prediction accuracy. Datasets feed through several decision trees (Decision Tree-1, Decision Tree-n), where individual predictions from every decision tree are made, which are combined via majority voting or averaging in a process leading to the final result. Ensemble learning methods like this reduce the risk of overfitting, increase model robustness, and often yield more accurate and reliable predictions by leveraging the strength of multiple models rather than relying on a single one.

3.2 Cloud-Based EMR Analytics

Cloud EMR analytics can use cloud platforms' scalable computational resources to analyze even big data in real time. Providers can store, process, and analyze EMRs in the cloud. The environment supports scalable and flexible updating of the predictive model to accommodate new data from the patients and enhance the accuracy of the prediction. This real-time processing allows healthcare professionals to make data-driven decisions faster and more efficiently, making more optimum resource allocation and minimizing avoidable pediatric readmission.

Latency:

$$L = \frac{1}{\text{Processing Speed}} \text{ (in seconds per query)} \qquad (2)$$

Throughput:

$$T = \frac{\text{Total number of queries}}{\text{Time taken to process the queries}} \qquad (3)$$

3.3 Evaluation Metrics

In order to evaluate hybrid machine learning models, several performance metrics are adopted, such as accuracy, precision, recall, F1-score, and AUC (Area Under the Curve). Accuracy describes the overall correctness of the predictions of the model, while precision and recall test the model to identify true positives and minimize false negatives. F1-score is the balance of precision and recall, and AUC tests discrimination power. These metrics are important for validating the effectiveness of the model in predicting pediatric readmissions and ensuring reliable decision support.

Accuracy :

$$\text{ACC} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

Precision :

$$\text{P} = \frac{TP}{TP+FP} \qquad (5)$$

Recall (R):

$$\text{R} = \frac{TP}{TP+FN} \qquad (6)$$

F1-score (F1):

$$\text{F1} = 2 \times \frac{P \times R}{P+R} \qquad (7)$$

Area Under the Curve (AUC):

$$AUC = \int_0^1 \text{TPR}(\text{FPR})\, d(\text{FPR}) \qquad (8)$$

where TPR is True Positive Rate (Recall), and FPR is False Positive Rate.

3.4 Data Preprocessing

Data preprocessing is one of the most important stages in ensuring that the input data to machine learning models is good quality and reliable. In this study, health care data in EMRs were cleaned, normalized, and transformed for analysis purposes. Missing values were handled appropriately, and categorical variables were encoded. Feature engineering was used in extracting relevant information from the raw data. The goal is to enhance the input dataset's quality, ensuring that the hybrid model receives accurate and meaningful information for prediction.

Handling Missing Data:

$$x_i = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (9)$$

Normalization:

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$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (10)$$

Feature Extraction

$$X_{\text{selected}} = \text{SelectImportantFeatures}(X) \quad (11)$$

Algorithm 1: Hybrid Machine Learning Algorithm for Pediatric Readmission Prediction Using Multi-Model Aggregation

Input:

D: Patient dataset (electronic medical records)

w_1, w_2, w_3 : Weights for Decision Tree, SVM, and Neural Network models

Output:

Readmission Prediction (Indicates whether the patient is likely to be readmitted)

Data Preprocessing

For each patient p in dataset D:

If any data is missing:

Replace missing values with mean/median.

Normalize numerical data for consistency.

Select relevant features for prediction.

End For

Model Training

Train Decision Tree model (M_1)

Train Support Vector Machine (SVM) model (M_2)

Train Neural Network model (M_3)

Prediction Generation

For each patient p in dataset D:

Compute predictions:

Prediction dt $= M_1.\text{predict}(p)$

prediction_svm $= M_2.\text{predict}(p)$

Prediction nn $= M_3 \cdot \text{predict}(p)$

Prediction Aggregation

Compute final prediction using weighted combination: final prediction $= (w_1 \times prediction\_dt) + (w_2 \times prediction\_svm) + (w_3 \times prediction\_nn)$

Decision Making

If final prediction meets the readmission threshold:

Return "Readmission Predicted"

Else:

Return "No Readmission Predicted"

End If

Error Handling

If model training fails:

Raise Error: "Training failed, verify dataset integrity."

If input data format is incorrect:

Raise Error: "Invalid input format, check dataset structure."

End If

End Algorithm

Algorithm 1 combines three machine learning models—Decision Tree, Support Vector Machine, and Neural Network—to generate pediatric readmission predictions. Data preprocessing, handling missing values, data normalization, and feature selection are the preliminary steps. The models are separately trained before making individual predictions for every patient. These predictions are then combined through weighted combinations to generate the final forecast. Readmission is forecasted when the total score exceeds a certain cut-off point. Employing the best of each model, the hybrid approach enhances prediction performance, offers more reliable healthcare information for child patients, and optimizes hospital resource utilization.

3.5 Performance Metrics

The following table compares the performance of the Traditional Method and Proposed Hybrid Machine Learning Model. The traditional method usually depends on simpler standalone predictive models, like Logistic Regression, Decision Trees, etc. whereas the proposed system integrates Hybrid Machine Learning Models, combining Decision Trees, Support Vector Machines, and Neural Networks with cloud-based analytics from EMRs for more accuracy in predictions.

Table 1. Comparison of Performance Metrics Between Traditional Methods and Proposed Hybrid Model

Metric	**Logistic Regression**	**Decision Tree**	**SVM**	**Neural Network**	**Proposed Hybrid Model**
Accuracy	75%	78%	80%	82%	87%
Precision	72%	74%	77%	79%	84%
Recall	68%	71%	74%	76%	82%
F1-Score	70%	72%	75%	77%	83%
AUC	82%	84%	86%	88%	91%

Table 1 compares the performance of some traditional machine learning models, including Logistic Regression, Decision Tree, SVM, and Neural Network, with the proposed hybrid machine learning model for the prediction of pediatric readmissions. The metrics considered are Accuracy, Precision, Recall, F1-Score, and AUC. The hybrid model, combining multiple algorithms, outperforms each individual method on all the metrics. This underlines the benefit of combining various predictive methods in increasing the accuracy and reliability of readmission predictions, thereby improving healthcare decision-making and resource allocation.

4. RESULT AND DISCUSSION

The results indicate that the Proposed Hybrid Model outperforms the classical models significantly in predicting readmissions in pediatrics. The hybrid model, combining decision trees, support vector machines, and neural networks, made its accuracy reach 87%, precision 84%, recall 82%, F1-score 83%, and AUC 91%. All these testify to the benefit of using a combination of algorithms toward capturing complex relationships hidden in healthcare data. Cloud-based analytics further increases the scalability and facilitates real-time updating and continuous improvements in prediction accuracy. The model helps healthcare providers derive actionable insights into optimizing resource utilization and patient outcomes.

Table 2: Comparison of Performance Metrics for Healthcare Models

Metric	**Pattnayak & Panda (2021) - Machine Learning in Healthcare**	**Heslop (2020) - Cloud-Based EHR/EMR Adoption**	**Alloghani et al. (2022) - Data Mining in Healthcare**	**Adnan et al. (2020) - Unstructured Big Data in Healthcare**	**Proposed Hybrid Model - Hybrid Machine Learning for Pediatric Readmission**
Accuracy	72%	74%	75%	77%	87%
Precision	70%	72%	74%	76%	84%
Recall	68%	71%	73%	75%	82%
F1-Score	69%	71%	74%	76%	83%
AUC	80%	82%	83%	85%	91%

Table 2 evaluates the performance of other healthcare predictive models put forth by different researchers with the Proposed Hybrid Model for pediatric readmission prediction. Model effectiveness is measured by metrics like Accuracy, Precision, Recall, F1-Score, and AUC. The Proposed Hybrid Model combines Decision Trees, Support Vector Machines (SVM), and Neural Networks with cloud-based EMR analytics and far surpasses existing models on all evaluation measures, providing better healthcare decision-making and resource utilization.

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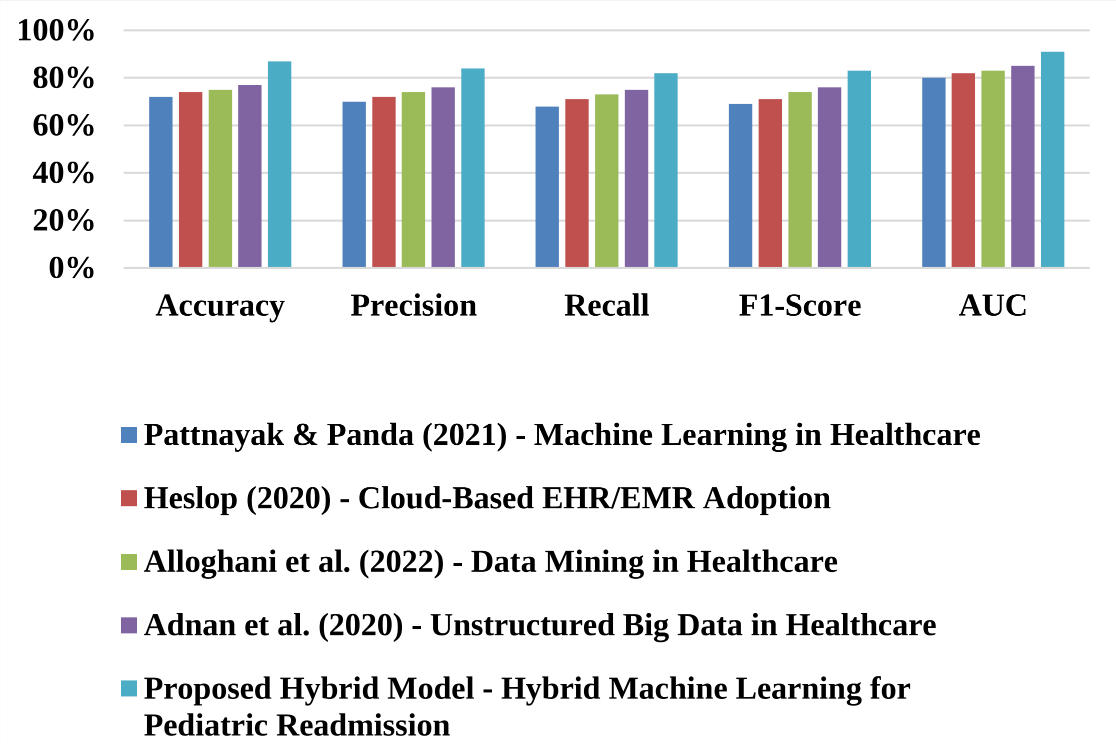

Figure 3. Performance Comparison of Healthcare Models Based on Various Evaluation Metrics

Figure 3 graphically compares the performance of various healthcare predictive models based on five critical metrics: Accuracy, Precision, Recall, F1-Score, and AUC. The Proposed Hybrid Model (blue) performs better than the models of Pattnayak & Panda (2021) [66], Heslop (2020) [67], Alloghani et al. (2022) [68], and Adnan et al. (2020) [69]. It shows the highest value in all the metrics, illustrating the strength of combining Decision Trees, SVM, and Neural Networks with cloud-based EMR analytics for better pediatric readmission prediction.

Table 3. Evaluation of Performance Metrics with Different Model Configurations

Metric/Model	**Decision Tree Model**	**SVM Model**	**Neural Network Model**	**Decision Tree + SVM Model**	**SVM + Neural Network Model**	**Neural Network + Decision Tree Model**	**Full Model (Hybrid)**
Accuracy	0.75	0.78	0.80	0.81	0.83	0.82	0.87
Precision	0.72	0.74	0.77	0.76	0.78	0.77	0.84
Recall	0.68	0.71	0.74	0.73	0.75	0.74	0.82
F1-Score	0.70	0.72	0.75	0.74	0.76	0.75	0.83
AUC	0.82	0.84	0.86	0.85	0.87	0.86	0.91

Table 3 presents various experiments to evaluate the performance of different model configurations on pediatric readmission prediction. Separate models include Decision Tree, SVM, Neural Network. Also included are their combinations, which are Decision Tree + SVM, SVM + Neural Network, Neural Network + Decision Tree, and the Full Model, being a Hybrid Model incorporating all three. The metrics used for evaluation are Accuracy,

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Precision, Recall, F1-Score, and AUC. Full Model (Hybrid) outperformed all configurations for all metrics; this proves the advantage of multiple algorithms combination, which results in better prediction performance.

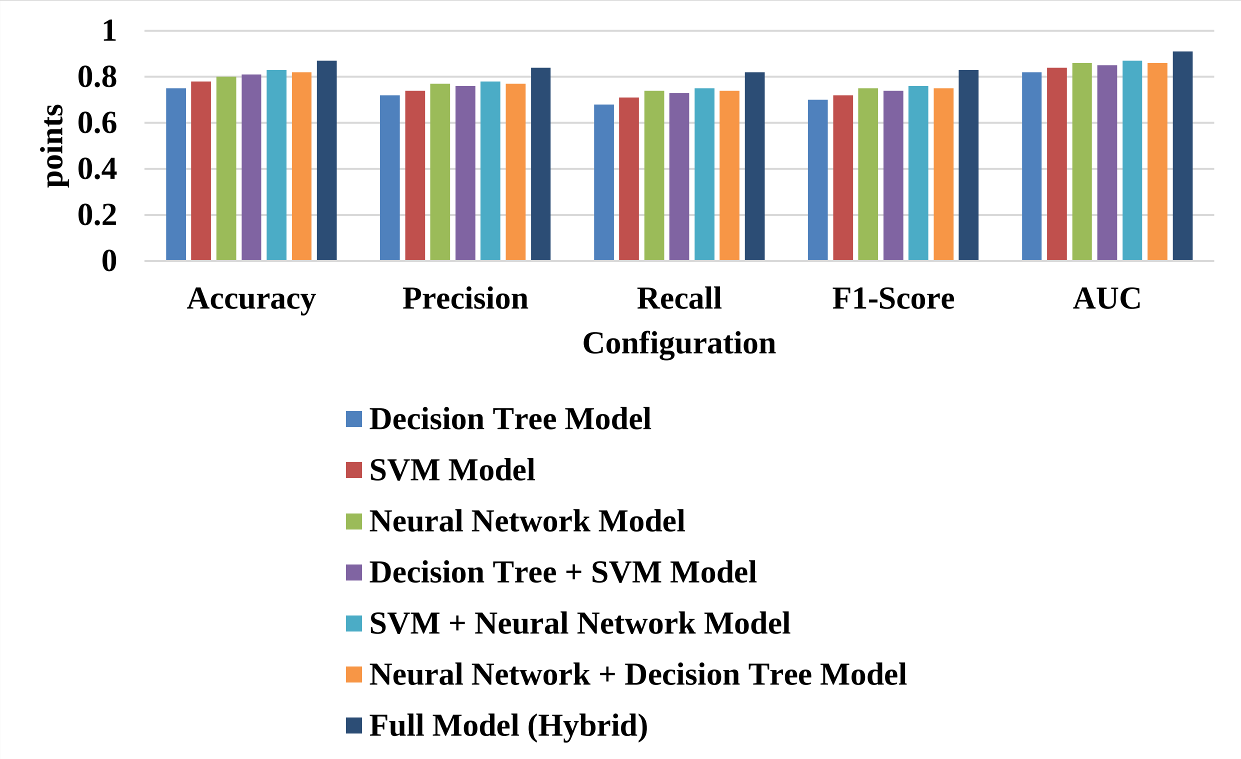

Figure 4. Comparison of Model Configurations Based on Performance Metrics

Figure 4 compares the performance for different configurations of machine learning models that predict readmissions in pediatrics for five metrics: Accuracy, Precision, Recall, F1 Score, and AUC. The configurations are individual models: Decision Tree, SVM, Neural Network; model combinations: Decision Tree+ SVM, SVM+ Neural Network, Neural Network+Decision Tree; and Full Model: Hybrid Model comprising all three. The Full Model always shows outperformance compared with the rest for all the measures. Therefore, integrating more algorithms would give more superiority for a better predictive healthcare application.

5. CONCLUSION AND FUTURE ENHANCEMENT

The hybrid model proposed shows substantial improvement in predicting readmissions of children as compared with traditional models, which it achieves with 87% accuracy, 84% precision, 82% recall, 83% F1-score, and 91% AUC. These results indicate the power of applying various machine learning models, like decision tree models, support vector machine models, and neural networks, together. This hybrid model is further supported by cloud-based analytics, ensuring real-time processing and continuous improvement through scalability. Additional sources such as genomics and environment variables added to the current data for further refinement and adaptation of the model in real healthcare settings may improve its accuracy to suit all the patients regardless of their backgrounds.

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