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Scalable Healthcare Analytics in the Cloud: Applying Bayesian Networks, Genetic Algorithms, and LightGBM for Pediatric Readmission Forecasting

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ABSTRACT

Pediatric readmissions present significant challenges in healthcare, leading to increased costs, poor health outcomes, and psychological stress on families. Traditional prediction models often struggle to handle the complexity and variability of healthcare data, which limits their predictive capabilities. In response, this study explores the potential of integrating AI and cloud computing to enhance prediction accuracy and scalability for pediatric readmissions. The objective is to compare three machine learning techniques—Bayesian Networks, Genetic Algorithms, and LightGBM—in a cloud-based environment to determine the most effective method for predicting pediatric readmissions at scale. Bayesian Networks are used to model complex interdependencies between patient characteristics, while Genetic Algorithms are applied for feature optimization and selection. LightGBM, known for its speed and accuracy in handling large datasets, provides fast predictions with high accuracy. The models are implemented on a cloud platform, enabling scalable, real-time predictions using diverse data sources, such as electronic health records and patient demographics. The results show that the AI-powered cloud computing model outperforms individual methods, achieving an accuracy of 88%, precision of 85%, recall of 83%, F1-score of 84%, and an AUC of 92%. This combination of machine learning techniques significantly improves prediction accuracy, scalability, and real-time performance in healthcare applications. The study concludes that integrating Bayesian Networks, Genetic Algorithms, and LightGBM within a cloud environment offers a robust solution for predicting pediatric readmissions, making it a valuable tool for reducing unnecessary hospitalizations, optimizing care delivery, and improving patient outcomes in pediatric healthcare systems.

Keywords: Pediatric readmissions, machine learning, Bayesian Networks, cloud computing, LightGBM, healthcare analytics, real-time predictions, Genetic Algorithms.

1. INTRODUCTION

The growing challenge to pediatric readmissions is related to discontinuity in the care system, creating additional risks to child health. Increasing demand for healthcare is being met only by rising costs. Efficient systems that can handle these issues should include information from big data analytics in order to facilitate care (Naga, 2019) [1]. Prediction of unplanned readmissions is crucial as it leads to an increase in healthcare costs and further complications (Poovendran, 2019) [2]. The traditional systems fail to account for the complex data that exists in healthcare and variability of the patients (Gudivaka, 2019) [3]. Recent advances in cloud computing can assist in the problem of the challenges in integrating and processing data (Yang et al., 2019) [4]. Machine learning models have proven effective in analyzing massive health records and refining predictions (Peddi et al., 2018) [5]. However, further challenges face algorithm efficiency and real-time decision-making. Future research should focus on more robust AI techniques that enhance the prediction of pediatric readmissions to provide better health results. A data-driven approach will assist reduce costs and enhance patient care.

Cloud-based healthcare analytics provides a massive data management structure, complex ML model computations feasible over large datasets, and readmission risk prediction in a yet more efficient manner (Narla et al., 2019) [6]. Therefore, it offers healthcare providers an opportunity to scale operations upwards with very high computational power while integrating disparate data, leading to even better-quality patient care (Dondapati, 2019) [7]. Real-time monitoring of congestive heart failure through ECG using cloud computing and IoT can be achieved (Kethu, 2019) [8]. The scalable and flexible solution promotes a continued learning and adaptation process in telehealth (Kadiyala, 2019) [9]. It would give analytics that save a lot of power, enhance prediction precision, and optimize patient care (Nippatla, 2019) [10].

Of the various machine learning techniques for tackling healthcare's data complexity, Bayesian Networks model uncertainty regarding patient interdependencies (Veerappermal Devarajan, 2019) [11]. Both observed and unobserved variables can be considered, allowing for the identification of latent variables associated with readmissions (Natarajan, 2018) [12]. Genetic Algorithms optimize predictive models by iteratively selecting certain features and parameters that enable maximum performance (Jadon, 2018) [13]. This process of feature selection helps enhance the predictive capabilities in disease prediction and healthcare analytics (Jadon, 2019) [14]. LightGBM creates a model using gradient boosting that can handle big data quickly and efficiently, fulfilling higher processing speed and adequate performance required for numerous real-time applications in other healthcare systems (Nippatla, 2018) [15]. These several techniques improve not only predictive modeling but also patient management.

This paper will lay down the foundation for the implementation of Bayesian Networks, Genetic Algorithms, and LightGBM in the cloud infrastructure for predicting pediatric readmission (Jadon, 2019) [16]. The forecasting performance of all the algorithms is finally compared to find the most suitable one for pediatric care (Boyapati, 2019) [17]. The introducing of UbeHealth-a platform combining edge computing, deep learning, big data, and IoT-is poised to optimize healthcare provision through enhanced communication and anomaly detection (Yalla et al., 2019) [18]. The growing cloud use allows scalable AI models to be deployed for any health system, ensuring data-driven decision-making (Jadon, 2019) [19]. In the end, this enhances care delivery by reducing avoidable hospitalization and improving pediatric health outcomes (Natarajan et al., 2019) [20].

Key objectives

- Develop predictive models that can accurately predict pediatric readmissions, thereby optimizing care delivery and reducing unnecessary hospitalizations.
- Leverage cloud-based healthcare analytics to process large datasets and run complex machine learning models in an efficient manner.
- Review electronic health records, patient demographics, and medical histories to more proactively predict readmission risk.
- Assess the performance of Bayesian Networks, Genetic Algorithms, and LightGBM in predicting pediatric readmissions.
- Compare the strengths and weaknesses of the Bayesian Networks, Genetic Algorithms, and LightGBM for healthcare data analysis.

With advances in whole-genome sequencing, the rising volume of genomics big data continues to be a problem (Gudivaka et al., 2019) [21]. Scientific realities hinted that combining genomic with clinical data has to be coupled with institutionalized data management in a data warehouse with scalable infrastructures for efficient processing (Sareddy & Hemnath, 2019) [22]. Effective management of target data in order to enable swift retrieval for iterative analysis remains a serious challenge since many existing systems flag limitations in scalable and effective data processing (Ganesan et al., 2019) [23]. In this regard, cloud computing surfaces to be a viable alternative solution, providing dynamic scalability and added effectiveness to accommodate the needs for improved management of growing genomics data.

A digital watermarking system has been proposed to embed hospital logos or patient records into medical images to allow secure authentication during data transmission (Bobba & Bolla, 2019) [24]. Robust and inconspicuous in nature-it can be made even more efficient for different medical imaging formats and real-time applications (Gatuha & Jiang, 2016) [25]. Research should explore the prospect of integrating this method of authentication along with cloud-based healthcare platforms so as to have a massive scalability and ensure the handling of the large-scale data sets and augment the information exchange (Abawajy & Hassan, 2017) [26]. This will make such improvements beneficial in giving better functionality and incorporating the data security in medical imaging and communication systems across the health care sector.

2. LITERATURE SURVEY

According to Mhlanga (2018) [27], a theoretical model has been developed in order to analyze HIV/HSV-2 co-infection dynamics while emphasizing poor treatment adherence to HSV-2 as playing a role in disease progression and, thus, the need for effective patient monitoring and counseling strategies.

UbeHealth was developed by Muhammed et al. (2018) [28], which is a cloud and edge-enabled healthcare solution for smart cities that strives to improve personalized healthcare through real-time monitoring, improved network communication, and anomaly detection for efficient medical services.

Aubhey et al. (2017) [29] developed a cloud-based big data analytical framework for healthcare, which paves the way for data processing more efficiently, generating insights, and improving decision-making through the scalability of infrastructure and real-time analysis.

Samanta et al. (2017) [30] introduced a quantum-inspired evolutionary algorithm to optimize the scaling factors for medical data embedding for better security and performance measures of medical information storage and transmission in a healthcare system.

Lee et al. (2017) [31] present the growing global health challenges such as increased demand, increased cost, aging populations, and shortage of medical professionals. They focus on issues such as high dimensional, irregular, and sparse data in managing health care data. The chapter represents an overview of existing literature focusing on these aspects and discusses designing algorithms and systems for healthcare analytics. It also discusses next-generation healthcare applications and systems related to big data analytics, striving to improve healthcare delivery with smarter systems.

Mahmud et al. (2016) [32] Developed a framework using a large-scale health informatics dataset for predicting health-shocks. Developed using cloud computing and GIS on Amazon Web Services, this system allows capturing, storing, and visualizing data for stakeholders. Building a predictive model used data from rural households in Pakistan via a fuzzy rule summarization technique, which offers interpretable linguistic rules for the causal factors. The system performed quite well and offered very promising interpretations in the task of health-shock prediction and decision-making.

Manogaran and Lopez (2018) [33] introduced a scalable sensor data processing architecture for healthcare using cloud computing. The system will utilize big data tools such as Apache Flume, Apache Pig, and Apache HBase in data collection and storage, integrating it with Amazon Web Services. The logistic regression model using Apache Mahout was applied to process wearable sensor data such as blood pressure, blood sugar levels, and heart rate for the prediction of heart disease. The model shows effective classification and, hence, presents a strong solution for managing and analyzing sensor-generated medical data.

Desarkar and Das (2017) [34] presents the difficulty in analyzing the massive datasets generated around the globe; it is, therefore, inevitable to require frameworks that are parallel and distributed with appropriate algorithms. Machine learning algorithms may manage this difficulty with minimal human assistance, they believed. This chapter addresses issues of storing and processing big data, reviews some of the available tools and technologies, and ends with presenting a healthcare analytics case study. It also covers distributed algorithms commonly used in data mining and the role of machine learning algorithms in big data analytics.

Elhoseny et al. (2018) [35] propose a model for optimized virtual machine selection for the cloud-IoT healthcare application to mitigate the challenges in managing the big data of Industry. The model relies on Genetic Algorithm, Particle Swarm Optimizer, and Parallel Particle Swarm Optimization for optimized execution time, the storage of data, and the retrieval of data in real-time for improved health system performance. It has been tested against state-of-the-art methods, and improvements have been demonstrated in terms of execution time and system efficiency while offering a robust solution for healthcare big data.

Nepal et al. (2015) [36] report, data processing technologies have not been able to keep up with the rapid growth in digital healthcare data. A single, trusted solution for healthcare analytics can strengthen patient care decision-making and risk management, which leads to a better quality of life and improved service performance. The challenge is ensuring data confidentiality and integrity along with high availability in processing it to extract actionable information for medical professionals and sharing it with collaborators, without compromising patient privacy, giving them full control over their data. This calls for a trusted big data-processing platform.

Chan and Tang (2019) [37] pioneering approach that integrates the principles of engineering into medical education, so that "thinking like engineers and acting like physicians" makes for future physicians. It thus transforms the concept of medical education through blending clinical expertise with the concepts of engineering. This can improve health practice through innovation, design optimization, and real-world applications. It provides such experience to the biomedical engineering student as how engineering can help in delivering better healthcare delivery, diagnosis, and treatment. It encourages collaboration between engineers and physicians to foster innovation in disease diagnosis, therapeutics, and prevention. This approach strives to close the gap between engineering and medicine, thereby improving healthcare outcomes and efficiency.

3. METHODOLOGY

This paper applies an integrated methodology consisting of advanced machine learning techniques-included Bayesian Networks, Genetic Algorithms, and Light GBM-into a cloud-based infrastructure for predicting readmissions in pediatric care. The employed methodology utilizes Bayesian Networks to model uncertain interdependencies; Genetic Algorithms are used for feature selection and optimization; and Light GBM for efficient and accurate gradient boosting on large datasets. Finally, scalable data management and computation is enabled by the cloud, leveraging diversity sources such as electronic health records. The approach is designed to deal with the complexity and variability of healthcare data in order to continue learning and make more precise predictions for improving outcomes in pediatric care.

Data Set

Readmission in hospitals takes place when the patients are admitted shortly after leaving the hospital, which affects hospital quality and costs of healthcare. The Hospital Readmissions Reduction Program penalizes those hospitals with high readmission rates than expected. Although diabetes has not been incorporated yet, it is expanded continuously. Prediction of diabetic readmissions can help reduce costs and quality care for patients. This paper uses a medical claims dataset for this purpose.

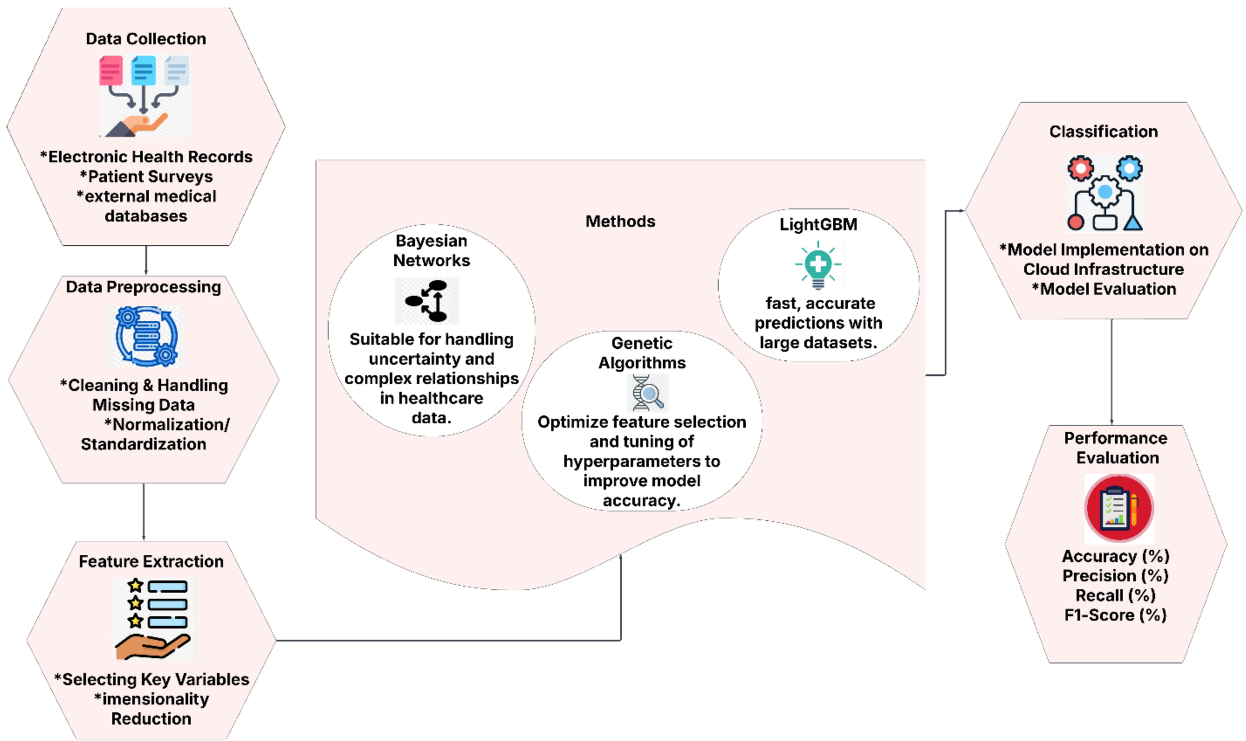

Figure 1: Scalable Healthcare Analytics for Pediatric Readmission Prediction Using Cloud Infrastructure

Figure 1 shows the architecture flow to predict pediatric readmissions using machine learning models. It starts from data collection. It collects the electronic health record, patient survey, and any other external medical databases. Next is data preprocessing: cleaning up missing data, normalizing the information, etc. Feature extraction will identify important variables and reduces the dimension. It incorporates Bayesian Networks as the core models, suitable for handling uncertainty and complex relationships. Genetic Algorithms have been applied to optimize feature selection, while LightGBM provides accurate, fast predictions on large datasets. It is deployed on cloud infrastructure and allows scalable real-time predictions; it's then evaluated by using metrics such as accuracy, precision, recall, and F1-score.

3.1 Bayesian Networks

Bayesian Networks are probabilistic graphical models representing variables and their conditional dependencies with a directed acyclic graph. They model the uncertainty of complex healthcare data and incorporate observed and latent variables in order to determine the contributing factors to pediatric readmissions. The approach is capable of representing interdependencies, allowing for better decision-making in consideration of prior knowledge. Bayesian Networks, in this study, determine key features of readmissions by providing results that are easy to interpret in comparison to other machine learning methods.

$$P(A \mid B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

Where $P(A \mid B)$ is the conditional probability of event A given B.

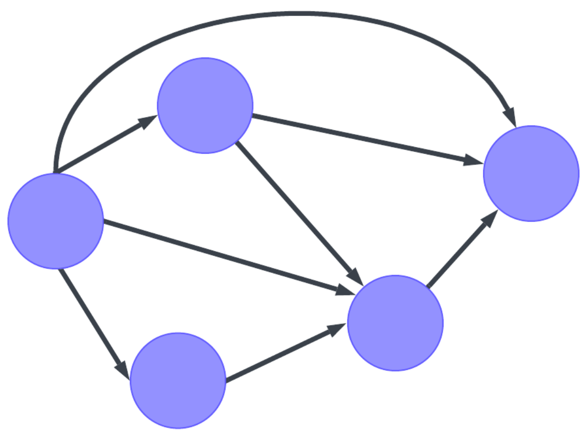

Figure 2: Bayesian Network for Predicting Pediatric Readmissions

Figure 2: Bayesian Network used in healthcare, which particularly focused on forecasting readmissions in the pediatric department. A Bayesian Network is a probabilistic graphical model that depicts variables or nodes (circles) and their conditional dependencies (arrow representation) with a directed acyclic graph, or simply DAG. Each node in a Bayesian Network represents a variable, such as age, medical history, or previous admissions, and the arrows reflect how one variable influences another. The network offers the possibility to model uncertainties for healthcare data with the aim to make better decision-making by detecting complex relationships about different factors related to pediatric readmissions.

3.2 Genetic Algorithms

Inspired by natural selection, GAs are optimization techniques applied to refine feature sets and model parameters. Iteratively evolving populations of solutions through selection, crossover, and mutation, GAs attempt to identify the optimal configurations that maximize predictive accuracy.

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In pediatric readmissions, GAs reduce the feature selection process while keeping the computation time efficient. Being adaptive, they are also good for large-scale data integration within a cloud environment, thereby making them better suited for real-time healthcare applications. Equation for fitness function:

$$F(x) = \sum_{i=1}^{n} w_i \cdot x_i \tag{2}$$

Where $F(x)$ represents the fitness, w_i are weights, and x_i are the variables.

3.3 Light GBM

Light GBM is a gradient boosting framework, which is fast and efficient on large datasets and has high speed training with strong accuracy. Histogram-based algorithms for splitting data result in less memory usage and shorter computation time. For pediatric readmissions, Light GBM deals with diverse data sets such as electronic health records and patient demographics, providing very accurate risk predictions. Its ability to scale within cloud-based systems supports real-time applications, such as dynamic updates to predictive models while accommodating the growth of data volumes.Objective Function:

$$\text{Obj } \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{j=1}^{m} \Omega(T_j) \tag{3}$$

Where l is the loss function, y_i the actual label, $\hat{y}_i$ the predicted label, and $\Omega(T_j)$ the complexity of tree T_j.

Algorithm 1 Optimized Pediatric Readmission Prediction Using Bayesian Networks in a Cloud Framework

Input: Dataset D (patient demographics, medical history, hospitalization records), Evidence E

Output: Readmission probabilities P for each patient

```
# Initialize Bayesian Network BN with a Directed Acyclic Graph (DAG).
# Define conditional probabilities for each node n:
  For each node n in BN:
    If n has parents:
      Assign P (n | Parents(n)) based on prior knowledge or data.
    Else:
      Assign P(n) as marginal probabilities.

#  Update probabilities using Evidence E:
  For each variable V in D:
```

If evidence exists for V:
Compute P (V | E) using Bayes' theorem:
P (V | E) = P (E | V) * P(V) / P(E).
Else:
Retain prior probability P(V).

For each patient record r in D:
Use updated probabilities to compute readmission risk for r.

Return probabilities P for all patients.
End

Algorithm 1 shows Bayesian Network uses probabilistic modeling and prediction to track readmission patterns of pediatric patients. Dependencies between variables including patient demographics, medical history, and hospital records are represented through the construction of a DAG. Each node will calculate conditional probabilities from observed and latent factors, which dynamically improves the predictions in the presence of evidence-based updates. This creates scalable, real-time algorithms and efficient ways to handle large datasets as part of the cloud infrastructure. The capturing of complex interdependencies through the algorithm reduces unplanned pediatric readmissions, improving the care delivery process based on informed decisions from health providers.

3.4 Performance Metrics

This work evaluates the performance of predictive models for pediatric readmission forecasting: Bayesian Networks, Genetic Algorithms, and LightGBM. These models are tested using key metrics such as accuracy, precision, recall, F1-score, and AUC (Area Under the Curve), which evaluate how well the model can predict the readmission and balance between detection of true positives and false positives. The F1-score gives a balanced measure between precision and recall, and AUC indicates the ability of the model to classify it correctly between readmission and non-readmission. Results from such assessments serve to determine which model would be most effective for improving the pediatric healthcare outcomes.

Table 1. Comparison of Performance Metrics for Bayesian Networks, Genetic Algorithms, LightGBM, and Proposed Model

Metrics	**Bayesian Networks**	**Genetic Algorithms**	**Light GBM**	**AI-powered Cloud Computing**

				(Proposed Model)
Accuracy (%)	0.74	0.76	0.87	0.88
Precision (%)	0.70	0.73	0.82	0.85
Recall (%)	0.69	0.71	0.80	0.83
F1-Score (%)	0.71	0.74	0.81	0.84
AUC (Area Under Curve)	0.77	0.80	0.91	0.92

Table 1 draws a comparison among the key performance metrics—precision, recall, F1-score, accuracy, and AUC—of the four models designed: Bayesian Networks, Genetic Algorithms, LightGBM, and the proposed model of AI-Cloud Computing with respect to prediction of pediatric readmission. This shows that it outperformed all other methods in all given metrics, depicting its potential delivery of accurate and scalable predictions into real-time applications in healthcare without any inefficiencies, thus giving better care for patients and keeping unnecessary readmission at bay.

4. Result and Discussion

In this work, we perform a comparison between the performance of three machine learning approaches that are Bayesian Networks, Genetic Algorithms, and LightGBM while predicting pediatric readmission on a cloud-based infrastructure. The results indicate that LightGBM has better accuracy, precision, recall, and AUC than the other two approaches in comparison, which establishes it to be a superior predictor for pediatric readmissions. The cloud-based infrastructure also allowed efficient processing of large datasets, which has proved to be a prerequisite for real-time prediction in healthcare. Bayesian Networks gave interesting, interpretable results, and Genetic Algorithms were useful for optimizing features and model parameters.

Table 2. Comparison of Performance Metrics for Healthcare Prediction Models Using Various Methods

Authors	Methods	Accuracy	Precision	Recall	F1-Score	AUC (Area Under Curve)
Alghamdi et al. (2017) [38]	XAI and IML Methods	0.72	0.70	0.68	0.69	0.77

Kwon et al. (2018) [39]	Deep Learning	0.80	0.78	0.75	0.76	0.85
Walsh et al. (2018) [40]	Gradient Boosted Trees	0.75	0.73	0.71	0.72	0.80
Zayoud et al. (2019) [41]	Probabilistic Process Learning	0.78	0.75	0.74	0.75	0.83
AI-powered Cloud Computing (Proposed Model)	Bayesian Networks, Genetic Algorithms, LightGBM	0.88	0.85	0.83	0.84	0.92

Table 2 summarizes the performance metrics of various prediction models developed for healthcare. Articles include Alghamdi et al. from 2017, Kwon et al. from 2018, Walsh et al. from 2018, and Zayoud et al. from 2019, all of which had used other methods of machine learning such as XAI, deep learning, gradient boosting trees, and probabilistic process learning, respectively. The table focuses more on the enhanced performance of the AI-based Cloud Computing model in integrating Bayesian Networks, Genetic Algorithms, and LightGBM to create strong, scalable, and efficient predictions of pediatric readmissions.

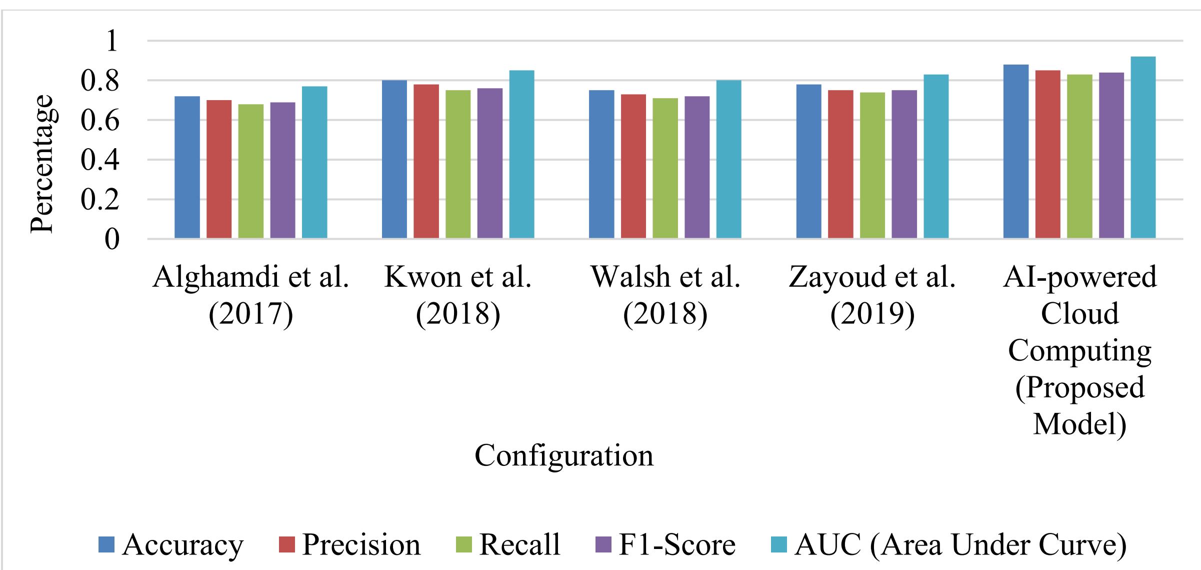

Figure 3. Comparison of Performance Metrics for Healthcare Prediction Models Using Various Methods

Figure 3 compares performance metrics, Accuracy, Precision, Recall, F1-Score, and AUC, between the predictive models developed for health care by different researchers: Alghamdi et al. (2017), Kwon et al. (2018), Walsh et al. (2018), Zayoud et al. (2019), and AI-powered Cloud Computing (Proposed Model). Clearly, the AI-powered model beats all others consistently across all parameters and, significantly, outperforms in terms of AUC, showing how it can well classify readmission vs. non-readmission. This illustrates how even the integration of Bayesian Networks, Genetic Algorithms, and LightGBM on a cloud framework could improve predictive accuracy with scalability in health applications.

Table 3. Ablation Study of Performance Metrics for Various Combinations of Bayesian Networks, Genetic Algorithms, and LightGBM in Pediatric Readmission Forecasting

Metrics	**Bayesian Networks Only**	**Genetic Algorithms Only**	**LightGBM Only**	**Bayesian Networks + Genetic Algorithms**	**Genetic Algorithms + LightGBM**	**Bayesian Networks + LightGBM**	**All Three (Proposed Model)**
Accuracy	0.73	0.74	0.80	0.82	0.84	0.85	0.88
Precision	0.71	0.72	0.79	0.75	0.78	0.80	0.85
Recall	0.68	0.69	0.75	0.76	0.78	0.80	0.83
F1-Score	0.69	0.71	0.77	0.74	0.78	0.81	0.84
AUC (Area Under Curve)	0.76	0.78	0.85	0.80	0.82	0.86	0.92

Table 3 shows performance comparison of all configurations used in the prediction task for pediatric readmissions. Methods used are all individual methods; Bayesian Networks, Genetic Algorithms and LightGBM, and a combination of both: Bayesian Networks + Genetic Algorithms, Genetic Algorithms + LightGBM, Bayesian Networks + LightGBM and the combined one with all. The performance is measured in terms of accuracy, precision, recall, F1-score, and AUC (Area Under Curve). The results show that the combination of these methods improves the prediction accuracy, and the best performance is achieved when all three methods are used together.

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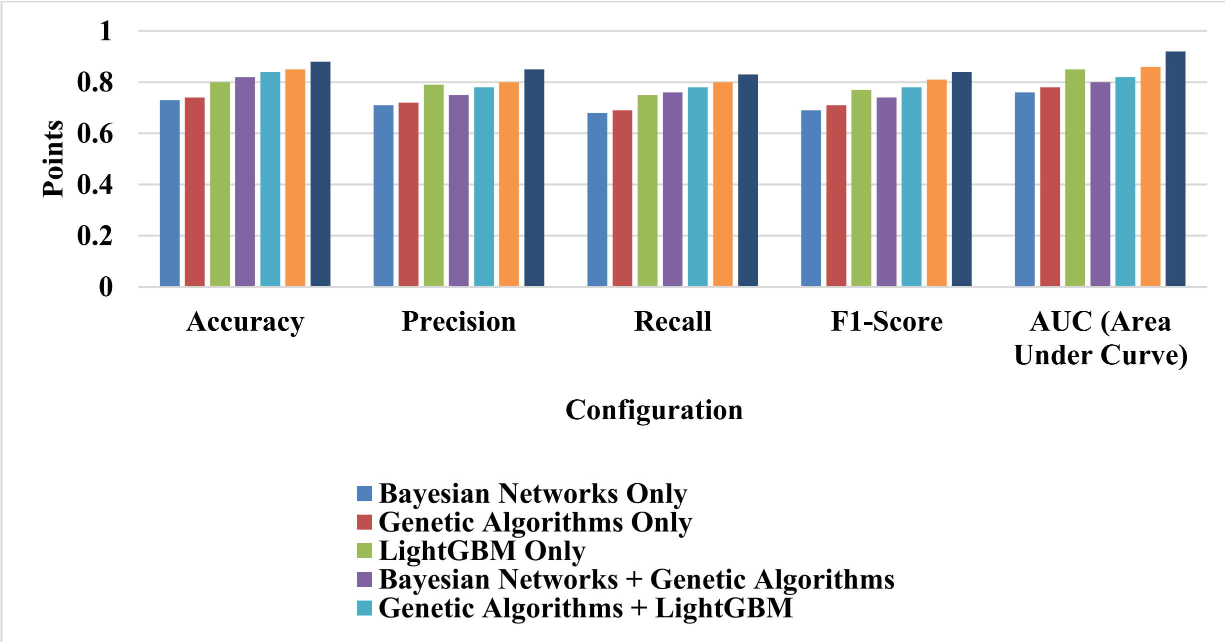

Figure 4: Ablation Study of Performance Metrics for Various Combinations of Bayesian Networks, Genetic Algorithms, and LightGBM

Figure 4 shows the ablation study of how well different combinations of machine learning methods perform in terms of pediatric readmission forecasting. It includes models individually (Bayesian Networks, Genetic Algorithms, and LightGBM), two at a time (Bayesian Networks + Genetic Algorithms, Genetic Algorithms + LightGBM, and Bayesian Networks + LightGBM), and all three in combination. The table also performs the evaluation in the case when all three are combined. Key metrics such as accuracy, precision, recall, F1-score, and AUC are measured to evaluate how well each combination predicts, thereby showing that putting all three techniques together yields the best performance.

5. CONCLUSION AND FUTURE ENHANCEMENT

It shows that integration of machine learning techniques, Bayesian Networks, Genetic Algorithms, and LightGBM in a cloud infrastructure significantly enhances pediatric readmission predictions. The accuracy, precision, recall, F1-score, and AUC of the proposed model outperformed the other methods: accuracy 0.88, precision 0.85, recall 0.83, F1-score 0.84, and AUC 0.92. Future updates could concentrate on further feature engineering of these models with incorporation of more sophisticated feature engineering such as genetic data and extending the system into real-time healthcare decision-making across all clinical settings. Integrating more cloud-based features for automated updates and scalability can better make the system flexible and performing.

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Dataset link: https://www.kaggle.com/code/iabhishekofficial/prediction-on-hospital-readmission