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AI-DRIVEN HEALTH INSURANCE PREDICTION USING GRAPH NEURAL NETWORKS AND CLOUD INTEGRATION

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ABSTRACT

The healthcare industry is rapidly evolving, with advancements in Artificial Intelligence (AI) and machine learning playing a crucial role in improving patient care and operational efficiency. However, challenges such as scalability issues, limited predictive accuracy, and complex system implementation remain prevalent in current healthcare prediction models. This work presents an AI-driven approach to health insurance prediction using Graph Neural Networks (GNNs) integrated with cloud computing to address these challenges. The workflow begins with data collection, involving patient demographics, medical history, and wearable sensor data, this collected data is then passed through data preprocessing, where label encoding is applied to categorical variables and outliers are detected using the IQR method, resulting in clean and structured data for analysis. The pre-processed data is used for feature extraction, where statistical measures such as standard deviation and variance are calculated to capture the variability in the data, providing more meaningful input for model training. These extracted features are then used in model development, where GNNs are employed to learn complex relationships between the entities and improve predictive accuracy and scalability. The model is integrated into a cloud-based environment, allowing for seamless deployment and efficient processing of large datasets. The model's performance metrics include an accuracy of 99.44%, precision of 99.32%, sensitivity of 99.12%, specificity of 99.17%, and F-measure of 99.28%. The latency analysis reveals a linear increase, with latency reaching 417 ms for a 150 GB dataset. This work provides an effective and scalable solution for health insurance prediction, utilizing GNNs and cloud computing, which outperforms traditional methods in terms of both accuracy and computational efficiency.

Keywords: Health Insurance Prediction, Deep Learning, Graph Neural Networks (GNNs), Cloud Storage.

1 INTRODUCTION

The healthcare sector is undergoing a significant transformation, with digital technologies like Artificial Intelligence (AI) playing an essential role in enhancing healthcare delivery and management [1] [2]. AI-driven models, particularly in health insurance prediction, are providing opportunities for more personalized services and better decision-making [3] [4] [5]. Health insurers face the challenge of accurately predicting customer behaviour, assessing risks, and determining suitable policies [6] [7] [8]. Traditional insurance models are often rule-based or rely on simple data-driven methods, which are insufficient to capture the complex and dynamic nature of health data [9] [10]. The explosion of healthcare data, including customer demographics, medical records, and insurance history, presents both opportunities and challenges in predicting health insurance outcomes [11] [12] [13]. Leveraging advanced machine learning techniques can enable insurers to offer customized policies and mitigate risks more effectively [14] [15]. However, existing systems often fail to fully utilize the depth of this available data [16] [17].

Various existing methods have been proposed to predict customer behaviour and outcomes in health insurance [18] [19]. Traditional machine learning techniques, such as Logistic Regression, Decision Trees, and Random Forests, are commonly used for classification tasks [20] [21]. More recent approaches include Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Neural Networks (NN), which offer improvements in predictive accuracy [22] [23]. However, these models often have limitations in capturing the complex interactions between customer demographics, health data, and insurance features [24] [25]. Deep Learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been utilized, especially for feature extraction, but they require large amounts of labeled data and considerable computational resources [26] [27]. Moreover, these models often overlook the interdependencies present in the data, which can limit their overall effectiveness in real-world applications [28] [29]. As a result, while these methods perform well under certain conditions, they do not fully exploit the complex relationships inherent in health insurance data [30] [31].

The proposed framework addresses the limitations of existing methods by incorporating Graph Neural Networks (GNNs), which can model the complex relationships between customer attributes, health conditions, and policy details as a graph. GNNs excel in learning from structured data and capturing intricate dependencies that traditional methods often overlook. By integrating cloud computing for deployment, the proposed system ensures scalability and real-time predictions, overcoming the computational constraints of deep learning methods. The novelty of this study lies in its ability to leverage GNNs for health insurance prediction, offering a more robust, flexible, and scalable solution compared to traditional machine learning approaches.

The organization of the paper is as follows: Section 2 reviews related works in health insurance prediction. Section 3 describes the methodology. Section 4 presents the experimental results. Finally, Section 5 discusses the conclusion and future work.

2 LITERATURE SURVEY

The challenges in image processing, including high computational costs and memory requirements, proposing cloud computing as a solution to meet these demands. This approach helps healthcare organizations reduce costs by outsourcing computations while ensuring strong data protection [32]. Introduced a cyber-physical system for healthcare services, utilizing cloud and big data to enhance healthcare performance through real-time patient monitoring [33]. Developed a cloud-based Brain-Computer Interface (BCI) for seizure prediction, incorporating deep learning techniques for real-time EEG data analysis [34]. Explored privacy challenges in healthcare data analytics, focusing on privacy-preserving models and the trade-offs between privacy and model efficiency [35].

The proposed a system for secure sharing of personal health data using blockchain and cloud storage, ensuring user control and data quality [36]. Deep learning in mobile healthcare, using a convolutional neural network (CNN) for voice pathology detection [37]. A cloud-centric IoT framework for smart student health monitoring, focusing on disease prediction and response time optimization [38]. Advancements in diabetes monitoring, proposing a 5G-Smart Diabetes system integrating wearable technology, machine learning, and big data for personalized care and efficient treatment [39].

Human activity recognition in smart home healthcare using wearable sensors and deep learning techniques. They employed a smartphone inertial sensor-based approach, extracting features and applying kernel principal component analysis (KPCA) and linear discriminant analysis (LDA) for enhanced activity recognition [40]. The UbeHealth framework, which integrates edge computing, deep learning, big data, and IoT to overcome challenges such as latency and bandwidth in healthcare networks [41]. The application of cloud computing in medical imaging, emphasizing its scalability and accessibility, while highlighting data security concerns [42]. A smart healthcare framework using edge computing and deep learning for voice disorder assessment, achieving high accuracy and sensitivity [43].

Cloud computing's role in healthcare, particularly in medical imaging and bioinformatics, and highlighted the associated security and privacy issues [44]. The use of deep learning in health informatics, focusing on its ability to automate feature extraction and enhance predictive capabilities [45]. A cloud-based IoT healthcare system for disease diagnosis, showing superior performance in predicting disease severity compared to traditional methods [46]. A mobile-cloud solution for personalized medical monitoring, improving diagnostic accuracy and efficiency in electrocardiograph monitoring [47] [48].

While existing healthcare analytics methods have made significant strides, challenges remain in data security, scalability, and real-time processing. The proposed framework addresses these issues by utilizing Graph Neural Networks (GNNs) and cloud integration, offering a more robust and scalable solution for health insurance prediction, overcoming the limitations of traditional approaches.

2.1 Problem statement

While significant progress has been made in healthcare prediction systems, several critical challenges still remain, such as scalability issues, limited predictive accuracy, and complexity in implementation. Scalability issues occur when systems fail to manage large volumes of healthcare data, leading to performance bottlenecks [49]. Limited predictive accuracy arises from traditional models that struggle to capture the intricate relationships within healthcare data, resulting in suboptimal predictions [50]. Complexity in implementation emerges from the integration of cloud computing, IoT, and machine learning, which complicates deployment and maintenance [51]. The work is proposed to overcome these challenges by employing GNNs to improve scalability and predictive accuracy, while simplifying the system architecture with a cloud-based solution for processing.

3 METHODOLOGIES

The framework for the health insurance prediction system begins with data collection, where customer demographics, health information, and policy details are gathered to form the dataset. Next, data preprocessing takes place, where categorical data like gender and smoking status is encoded using label encoding, and outliers are detected and removed using the IQR method to ensure the data is clean and reliable for modelling. After preprocessing, feature extraction is performed by calculating statistical features such as standard deviation and variance to capture the variability in key variables like income and health metrics. The next step is model development, where Graph Neural Networks (GNNs) are trained to identify complex relationships between customer attributes, health conditions, and policy details for accurate predictions. Finally, the trained model is deployed in a cloud environment to ensure scalability, predictions, and easy updates, making the system robust and adaptable for ongoing use. The whole framework is illustrated in Figure 1.

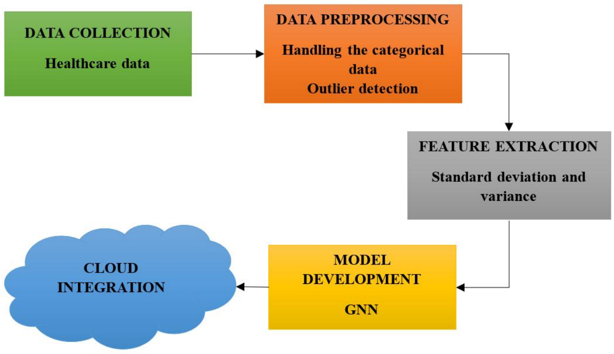

Figure 1: System Workflow for Health Insurance Prediction

3.1 Data Collection

Data collection for this work involves gathering diverse healthcare-related data from multiple sources, including patient demographics, medical history, and health records. Key data points include age, gender, lifestyle factors, and pre-existing conditions. Additionally, data from wearable IoT devices, such as heart rate, blood pressure, and glucose levels, is collected to provide health monitoring. Insurance-related data, including policy types, claims history, and coverage details, is also incorporated. This comprehensive dataset ensures that all relevant factors influencing health insurance decisions are considered for accurate predictions. The data is then processed and used to train the model for health insurance prediction.

3.2 Data Preprocessing

Data preprocessing begins with handling the categorical data collected from various sources such as patient demographics and insurance details. Label encoding is applied to convert categorical variables, like gender or smoking status, into numerical values. This transformation ensures that the data can be fed into machine learning models, which require numerical inputs for analysis.

The next step involves outlier detection, particularly for continuous variables like age, income, or health metrics. The Interquartile Range (IQR) method is applied to identify and remove extreme outliers that could skew the model's predictions. By removing these anomalies, the dataset becomes more reliable, allowing the model to focus on the general trends and patterns. This step ensures that the data is clean and well-prepared for training the predictive models, leading to improved accuracy and efficiency.

3.3 Feature Extraction

After preprocessing the data, feature extraction is performed using statistical measures such as standard deviation and variance. Standard deviation helps capture the dispersion or spread of the data points, indicating how much individual values differ from the mean. Variance, which is the square of the standard deviation, further quantifies the data's variability. These features are crucial for identifying patterns in health-related data, such as blood pressure or glucose levels, as they provide insights into how consistent or variable a patient's health metrics are. Extracting these features helps improve the model's ability to understand the variability in patient data, leading to more accurate predictions.

3.4 Model Development

After extracting features, model development is carried out using Graph Neural Networks (GNNs). GNNs are ideal for modelling complex relationships within the data, especially when the data involves interconnected entities, such as patients, medical conditions, and insurance policies. The extracted features are fed into the GNN, which captures dependencies between these entities and learns from their interactions. GNNs leverage their ability to process graph-structured data to provide more accurate predictions by understanding the connections and patterns across multiple variables. This approach enhances the model's ability to handle complex healthcare data, leading to improved accuracy in health insurance predictions.

The mathematical representation of GNNs in the context of the proposed model involves processing graph-structured data. In this case, the graph $G = (V, E)$ consists of nodes V representing entities such as patients, health conditions, insurance policies, and edges E representing relationships or interactions between these entities. The features extracted from the data, such as standard deviation and variance, are represented as node features $X \in \mathbb{R}^{|V| \times d}$, where d is the number of features for each node.

For each node $v_i \in V$, the GNN learns a hidden representation $h_i^{(l)}$ at the l-th layer, which is updated through a message-passing mechanism based on its neighbors in the graph and it's expressed as equation (1),

$$h_i^{(l)} = \sigma\left(W^{(l)} \cdot \left(h_i^{(l-1)} + \sum_{j \in \mathcal{N}(i)} \frac{1}{\sqrt{|\mathcal{N}(i)|}} \cdot h_j^{(l-1)}\right)\right) \tag{1}$$

Where, $\mathcal{N}(i)$ is the set of neighbors of node i in the graph. $W^{(l)}$ is the weight matrix at layer l. σ is an activation function. $h_i^{(l-1)}$ and $h_j^{(l-1)}$ are the feature vectors of node i and its neighbor j at the previous layer. This equation represents the message-passing mechanism in GNNs, where each node aggregates information from its neighbors in the graph. This process allows the network to learn from not just the individual features but also the relationships between entities

In the final layer, the learned node representations $h_i^{(L)}$ are used for the prediction task, such as classifying health insurance risk or predicting customer behavior. It's represented as equation (2),

$$y_i = f\left(h_i^{(L)}\right) \tag{2}$$

Where f is a prediction function, such as a softmax or linear regression, depending on the type of task. Where f is applied to $h_i^{(L)}$, is used to generate the final output, such as health insurance prediction, based on the learned graph representations.

By using GNNs, the model effectively captures the relationships between patients, health data, and policies, leading to more accurate and robust predictions.

3.5 Cloud Integration

After model development with Graph Neural Networks (GNNs), cloud integration is implemented to ensure scalability and e processing. The trained GNN model is deployed on cloud platforms, allowing it to handle large datasets and process requests from multiple users simultaneously. Cloud services provide the necessary computational power to run the model efficiently, while offering on-demand scalability to handle fluctuating workloads. This integration ensures that the model can process health insurance predictions, providing quick insights for decision-makers. Additionally, cloud storage is used to securely store patient data and prediction results, ensuring easy access and management. The cloud-based solution also supports regular updates to the model, allowing continuous improvement and adaptation to new data.

4 RESULTS

The results of the health insurance prediction model demonstrate its effectiveness in terms of both accuracy and efficiency. The performance metrics and latency analysis showcase the model's robustness in handling large datasets and delivering accurate predictions. This section presents the key results obtained from the evaluation of the model's performance.

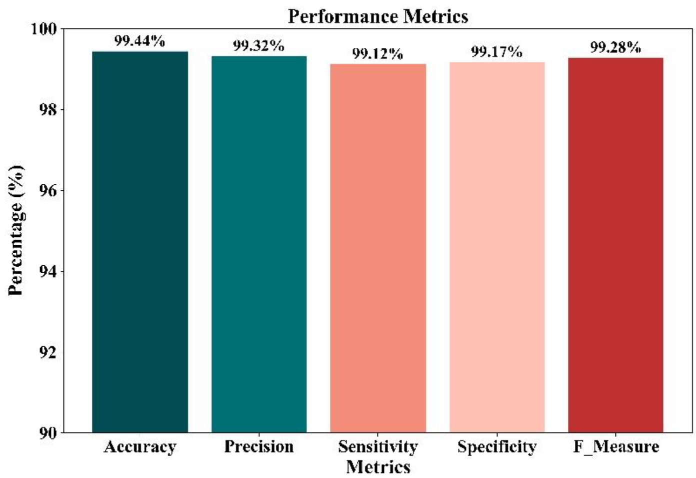

Figure 2: Performance Metrics

Figure 2 illustrates the performance metrics of the health insurance prediction model. The model achieves high values across various metrics: Accuracy (99.44%), Precision (99.32%), Sensitivity (99.12%), Specificity (99.17%), and F-Measure (99.28%). These results demonstrate that the model performs exceptionally well in predicting health insurance outcomes with minimal false positives and negatives. The high accuracy and F-measure indicate a balanced model, delivering both precise and reliable predictions. Overall, these performance metrics highlight the model's robustness and effectiveness.

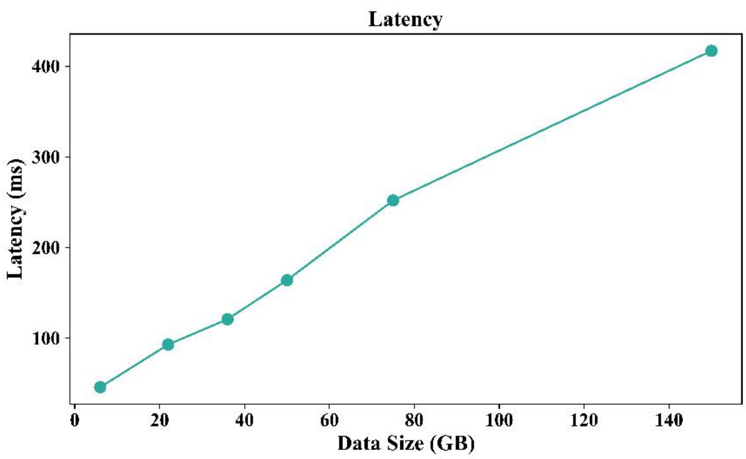

Figure 3: Latency

Figure 3 displays the relationship between data size and latency. As shown in the graph, there is a clear positive correlation: as the data size increases, the latency also increases. For example, when the data size is 6 GB, the latency is around 46 ms, while at 150 GB, it reaches 417 ms. This trend demonstrates the impact of larger data volumes on processing time. The model's latency grows progressively with data size, highlighting the computational challenges associated with handling larger datasets. These results emphasize the need for optimized processing techniques to manage latency effectively as data sizes increase.

5 CONCLUSIONS

This work achieved the goal of developing a scalable, accurate, and efficient health insurance prediction model using Graph Neural Networks (GNNs) integrated with cloud computing. The model demonstrated exceptional performance, with an accuracy of 99.44%, precision of 99.32%, sensitivity of 99.12%, specificity of 99.17%, and F-measure of 99.28%, indicating robust predictive capabilities. Additionally, latency analysis revealed a linear increase, with latency reaching 417 ms for a 150 GB dataset, showcasing the model's ability to efficiently handle large-scale data. The proposed approach leverages the power of GNNs to model complex relationships between health data and insurance variables, delivering highly accurate predictions. Cloud integration further ensures scalability and processing, allowing the model to adapt to large datasets and providing seamless deployment for practical applications. Future work could focus on utilizing reinforcement learning to allow the model to dynamically adapt to changes in health insurance data, optimizing predictions over time.

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