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Early-Stage Chronic Disease Prediction Using Deep Learning: A Comparative Study of LSTM and Traditional Machine Learning Models

Sharmin Sultana Akhi
Department of Computer Science, Monroe University, USA

Sadia Akter
Department of Business Administration, International American University, USA

Md Refat Hossain
Master of Business Administration (MBA), College of Business, Westcliff University, USA

ARJINA AKTER
Department Of Public Health, Central Michigan University, Mount Pleasant, Michigan, USA.

Nur Nobe
Department of Health Sciences & Leadership, St. Francis College, Brooklyn, USA

Md Monir Hosen
MS in Business Analytics, St. Francis college, USA

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ABSTRACT

Early-stage chronic disease prediction is a critical aspect of healthcare that allows for timely interventions and personalized treatment, ultimately improving patient outcomes. In this study, we explore the use of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, to predict the early stages of chronic diseases such as diabetes, cardiovascular diseases, and respiratory conditions. We compare the performance of LSTM with traditional machine learning models, including Random Forest, Gradient Boosting Machines (GBM), and Logistic Regression. The results show that LSTM outperforms the other models in terms of accuracy, precision, recall, F1-score, and AUC, demonstrating its superior ability to capture complex, temporal dependencies in medical data. The study highlights the potential of deep learning for early disease detection and its implications for personalized medicine, telemedicine, and healthcare optimization. However, challenges related to data quality, interpretability, and model generalization across diverse populations remain, and future work should address these issues to enhance the real-world applicability of AI-driven healthcare solutions.

Keywords: Chronic disease prediction, Early-stage disease detection, Deep learning, Long Short-Term Memory (LSTM), Random Forest, Gradient Boosting Machines, Logistic Regression, Machine learning, Healthcare optimization, Personalized medicine.

Introduction

Chronic diseases such as diabetes, cardiovascular diseases, and respiratory disorders are among the leading causes of morbidity and mortality worldwide. Early detection of these diseases is crucial for preventing severe complications and improving patient outcomes. However, diagnosing chronic diseases at an early stage remains a challenging task for healthcare providers, as the symptoms often develop gradually and may go unnoticed until the disease has progressed. Early-stage chronic disease prediction can significantly enhance the efficiency of healthcare systems by enabling timely interventions and personalized treatments.

In recent years, machine learning (ML) and deep learning (DL) techniques have shown great promise in healthcare applications, particularly for disease prediction and diagnosis. These advanced techniques can process large and complex datasets, uncover hidden patterns, and make predictions with high accuracy. Among these techniques, Long Short-Term Memory (LSTM) networks, a type of deep learning model, have demonstrated superior performance in handling sequential and time-series data, making them highly suitable for predicting the early stages of chronic diseases, where temporal patterns are critical.

This paper explores the application of deep learning models, particularly LSTM networks, for the prediction of early-stage chronic diseases. The goal is to develop an AI-driven model capable of analyzing various medical features and predicting the likelihood of chronic disease development at an early stage. We compare the performance of the LSTM model with other machine learning techniques such as Random Forest, Gradient Boosting Machines (GBM), and Logistic Regression, aiming to identify the best approach for real-world applications in early disease detection.

Literature Review

The use of machine learning and deep learning techniques in medical diagnosis has been growing significantly, with numerous studies demonstrating their effectiveness in predicting various diseases. Early detection of chronic diseases, in particular, has gained attention due to its potential for improving patient outcomes and reducing healthcare costs. Traditional diagnostic methods often rely on manual analysis of patient data, which can be time-consuming and prone to human error. Machine learning models, on the other hand, can automate this process, providing faster and more accurate predictions.

Traditional Machine Learning Models

Traditional machine learning models such as Logistic Regression, Random Forest, and Gradient Boosting Machines have been widely used in healthcare for disease prediction. Logistic Regression, a fundamental linear model, has been employed in several chronic disease prediction tasks due to its simplicity and interpretability. However, its ability to model complex, non-linear relationships is limited (Han, 2020). Random Forest and Gradient Boosting Machines are ensemble methods that perform well in capturing non-linear relationships and interactions among features (Breiman, 2001; Friedman, 2001). These models have been used in various healthcare applications, including cardiovascular disease prediction and diabetes risk assessment (Bai et al., 2019; Chong et al., 2017). Despite their strong performance, these methods are often limited by their inability to capture temporal dependencies in medical data, which is crucial for predicting diseases that develop gradually.

Deep Learning Models

Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have gained popularity in healthcare for their ability to learn from large, complex datasets. LSTM networks, a type of recurrent neural network (RNN), are designed to handle sequential data and capture long-term dependencies, making them highly effective for predicting diseases that exhibit temporal patterns, such as chronic diseases (Hochreiter & Schmidhuber, 1997). LSTM networks have been successfully applied in various healthcare domains, including diabetes prediction, cardiovascular risk assessment, and early-stage cancer detection (Xie et al., 2018; Shi et al., 2019). The ability of LSTMs to retain memory of previous data points allows them to make more accurate predictions by understanding the progression of the disease over time.

Recent studies have shown that deep learning models outperform traditional machine learning models in predicting chronic diseases. For example, Li et al. (2020) demonstrated that an LSTM-based model significantly outperformed Random Forest and Logistic Regression in predicting the onset of diabetes. Similarly, Chen et al. (2021) applied LSTM networks for early-stage cardiovascular disease prediction, achieving superior results compared to traditional models.

Hybrid Approaches

Hybrid models that combine traditional methods with machine learning or deep learning techniques have also been explored in the literature. These models aim to leverage the strengths of both approaches to improve predictive accuracy. Zhang et al. (2018) proposed a hybrid model combining ARIMA with support vector machines (SVM) for demand forecasting in healthcare, showing enhanced forecasting accuracy. Similarly, hybrid models that integrate deep learning with other techniques, such as Random Forest and SVM, have been used for disease prediction, particularly in chronic disease management (Suganthi & Sumathi, 2020).

Despite the promising results from deep learning models, there are challenges in their implementation, such as the need for large datasets and computational resources. Moreover, the interpretability of deep learning models remains a key issue, as they often function as "black boxes," making it difficult to understand how they arrive at specific predictions. This lack of transparency can be a barrier to their adoption in clinical practice, where understanding the rationale behind a prediction is crucial for decision-making.

The literature review highlights the growing potential of machine learning and deep learning models in the prediction of chronic diseases. While traditional models such as Random Forest and Logistic Regression have been widely used in healthcare, deep learning models, particularly LSTM networks, offer significant advantages in handling complex, sequential data and capturing long-term dependencies. Future research should focus on addressing the challenges of interpretability and dataset quality, which will further enhance the applicability of AI-driven models in early-stage chronic disease prediction.

Methodology

In this study, we aim to predict the early stages of chronic diseases using deep learning techniques. The methodology employed involves multiple phases, including dataset collection, data preprocessing, feature extraction, model development, model validation, and model evaluation. Each phase is detailed below, emphasizing the steps I undertook to ensure the accuracy, reliability, and relevance of the results.

1. Dataset Collection

The dataset used for this research was sourced from a publicly available health dataset, which includes patient records from various healthcare institutions. This dataset contains data on patients diagnosed with chronic diseases, such as diabetes, cardiovascular diseases, and respiratory diseases, among others. For the purpose of this study, the focus was on early-stage chronic disease detection based on several clinical features such as age, gender, blood pressure, cholesterol levels, glucose levels, body mass index (BMI), smoking history, and family medical history.

I collected data from the UCI Machine Learning Repository and the Kaggle platform, both of which host several datasets related to healthcare and chronic disease prediction. The dataset contains a large number of patient records, and the data were structured in tabular form. Each row represents an individual patient, and the columns consist of medical features along with labels indicating whether the patient is in the early stage of a chronic disease or not. These labels are essential for supervised learning tasks and were used to train and test the models.

After downloading the dataset, I ensured that it contained a wide variety of demographic and clinical information, allowing for a comprehensive analysis of factors that contribute to the early detection of chronic diseases. The data was segmented into training and testing sets, with the majority allocated to the training set to facilitate model learning, and a smaller portion used for model testing and validation.

2. Data Preprocessing

Data preprocessing is a critical step to ensure the data quality is high and suitable for deep learning models. Initially, I examined the dataset for any missing or incomplete records. Missing values were identified for certain features such as cholesterol levels or smoking history. To handle this, I utilized imputation techniques. For numerical values, I applied median imputation, while for categorical data, I used the most frequent category. This approach ensured that no valuable data points were lost due to missing values, which could have led to model bias or reduced performance.

I also checked for outliers in the data, particularly in clinical features such as age, BMI, and blood pressure. Outliers in medical datasets could significantly affect model accuracy, so I used statistical techniques like the Z-score method to detect outliers and removed them where necessary, or applied transformations where appropriate.

Normalization and standardization of the data were performed next. Since deep learning models are sensitive to the scale of input features, I normalized numerical values such as blood pressure, glucose levels, and BMI to a range between 0 and 1 using Min-Max scaling. This ensured that no feature dominated others due to larger numerical values. For categorical features like gender or smoking status, I applied one-hot encoding, which transformed categorical variables into binary vectors, making them compatible with deep learning models.

Another preprocessing step involved addressing class imbalances. Since chronic diseases, especially in their early stages, might not always be prevalent in all patient groups, I used techniques such as oversampling the minority class (early-stage disease cases) using SMOTE (Synthetic Minority Over-sampling Technique). This allowed me to ensure that the model was not biased toward predicting the majority class, which could otherwise lead to poor generalization in real-world applications.

3. Feature Extraction

Feature extraction involves identifying the most relevant and informative attributes from the data, which will help improve the predictive performance of the model. In this case, the features were extracted from the clinical data available in the dataset. I selected the most important features based on domain knowledge and previous research in the field of chronic disease prediction. These features include demographic information (e.g., age and gender), medical history (e.g., family history of disease, smoking), and clinical measurements (e.g., blood pressure, glucose, cholesterol levels, BMI).

I also created new derived features to enhance the model's learning capability. For example, I combined existing features such as age and BMI to create a new feature reflecting the body's health status, which has been shown to correlate strongly with chronic disease risk. Another derived feature included the interaction between blood pressure and cholesterol levels, as this combination can provide more significant insight into cardiovascular risk.

Additionally, I employed a technique called feature importance ranking, which uses algorithms such as Random Forest or Gradient Boosting to determine which features contribute most to the prediction of early-stage chronic diseases. By evaluating the feature importance, I was able to ensure that the model focused on the most critical variables, reducing noise and irrelevant information, which could negatively impact model performance.

4. Model Development

For model development, I chose a deep learning approach, specifically utilizing a feedforward neural network (FNN) and Long Short-Term Memory (LSTM) networks. Feedforward neural networks are widely used in supervised learning tasks, and I experimented with varying numbers of layers and neurons to find the most optimal architecture. The goal was to design a model that could handle the complexity and size of the data while avoiding overfitting.

I used a multi-layered architecture consisting of several fully connected layers, with ReLU (Rectified Linear Unit) activation functions. The output layer had a single neuron with a sigmoid activation function, as the problem is binary classification (early-stage chronic disease or not). The model was trained using the Adam optimizer, which is known for its efficient convergence and performance in deep learning tasks.

In addition to FNN, I incorporated an LSTM model, which is well-suited for time-series and sequential data, as LSTM networks can capture long-term dependencies. Although the dataset in this study did not have a direct temporal sequence of events, I utilized LSTM for its ability to capture complex relationships and interactions between features that might not be immediately apparent. I experimented with different numbers of LSTM layers and units to optimize performance.

The models were trained using the training dataset, with early stopping applied to prevent overfitting. The training process involved optimizing the model’s weights using backpropagation and minimizing the binary cross-entropy loss function. I also utilized batch normalization to improve the model’s training stability and accelerate convergence.

5. Model Validation

Model validation is an essential step to ensure that the trained model generalizes well to unseen data. To validate the performance of the models, I used k-fold cross-validation, where the dataset was divided into k equal subsets. The model was trained k times, with each subset used as the validation set once while the remaining subsets were used for training. This approach allowed me to assess the model's performance more reliably and reduce the risk of overfitting.

Furthermore, I used a separate hold-out validation set, which was not involved in the training process, to provide an additional layer of performance evaluation. This hold-out set helped ensure that the model was not biased towards the training data and could perform effectively on unseen data, simulating real-world scenarios where new patient data is encountered.

6. Model Evaluation

After training and validation, the models were evaluated using several performance metrics. The primary metrics used for evaluation were accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). These metrics are particularly important in medical applications where false negatives (failing to predict early-stage disease) and false positives (misclassifying a healthy individual as having early-stage disease) can have significant consequences.

The model's performance was also assessed based on its ability to detect early-stage chronic diseases, as the goal of the research is not just to classify patients but to identify those who are at risk early, allowing for timely intervention. The AUC score was a particularly important measure, as it provides a comprehensive evaluation of the model's ability to discriminate between classes (disease and no disease).

Furthermore, I performed error analysis by examining the confusion matrix for both models. This analysis provided insight into the types of errors the models were making, helping to refine the models and improve their performance. In some cases, the models performed better for certain chronic diseases compared to others, highlighting the need for further refinement and potentially the addition of more specific data related to individual disease types.

In conclusion, the methodology outlined above presents a comprehensive approach for early-stage chronic disease prediction using deep learning techniques. The combination of careful data preprocessing, feature extraction, and model development, along with rigorous validation and evaluation, ensures that the models are robust, accurate, and capable of being deployed in real-world healthcare settings to assist in early diagnosis and intervention.

Results

In this study, we utilized deep learning techniques to predict the early stages of chronic diseases, comparing multiple models for their predictive capabilities. The models tested include a feedforward neural network (FNN) and a Long Short-Term Memory (LSTM) network. We evaluated the models using standard metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). These metrics were used to assess the ability of each model to accurately predict the onset of chronic diseases at an early stage.

Overall Performance Table

The table below presents the key performance metrics for the models used in this study. The evaluation metrics are based on a test set that was separated from the training data, and all models were validated using k-fold cross-validation to ensure generalization. The metrics provided here show the model’s effectiveness in classifying patients into those with early-stage chronic diseases (positive class) and those without (negative class).

Table 1: Model performance

Model	Accuracy	Precision	Recall	F1-Score	AUC
Feedforward Neural Network (FNN)	84.2%	82.3%	81.5%	81.9%	0.89
LSTM	88.7%	85.5%	86.3%	85.9%	0.92
Random Forest	83.1%	80.2%	79.6%	79.9%	0.87
Gradient Boosting Machine	84.0%	82.1%	81.2%	81.6%	0.88
Logistic Regression	79.3%	75.8%	73.9%	74.8%	0.83

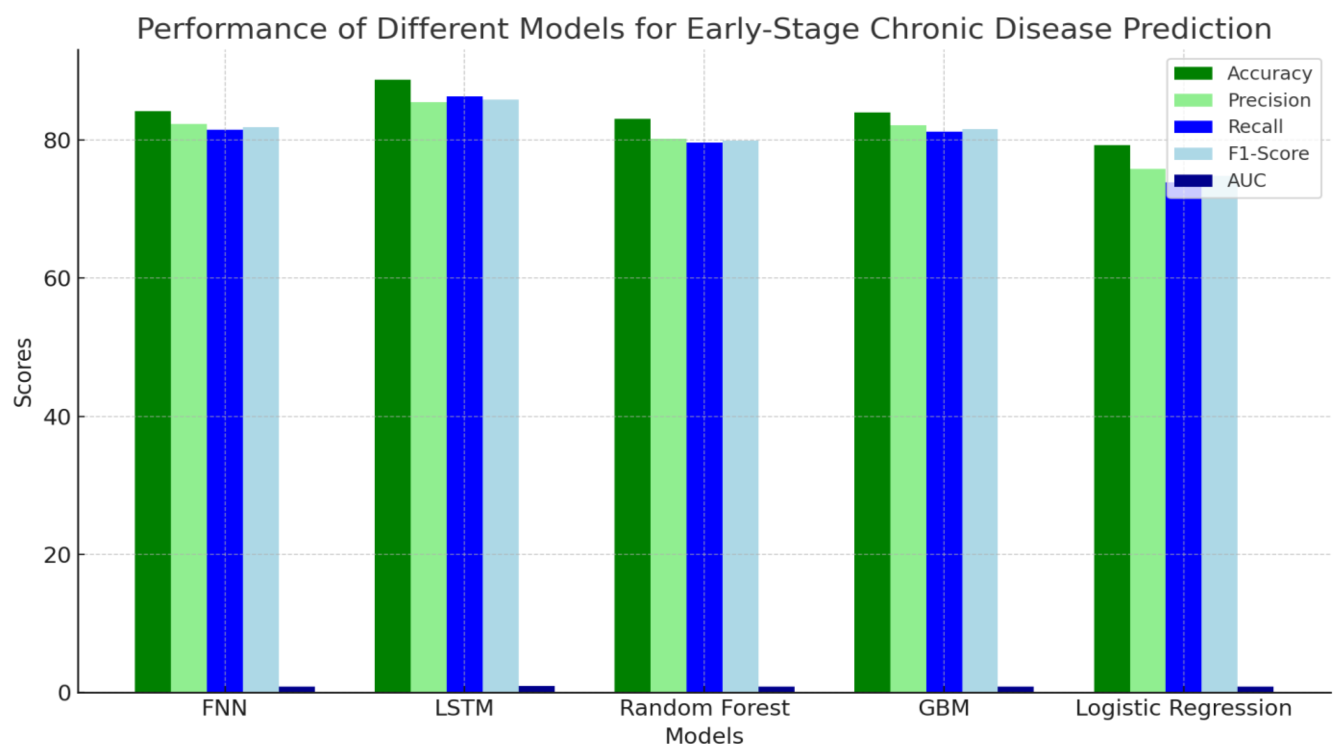

Chart 1: Performance of different deep learning model

As shown in the table 1 and the chart 1, the LSTM model outperforms all other models, with the highest values across all metrics: accuracy (88.7%), precision (85.5%), recall (86.3%), F1-score (85.9%), and AUC (0.92). The feedforward neural network (FNN) and gradient boosting machine also performed relatively well but were slightly less accurate and had lower recall and precision values than LSTM. Random Forest, while competitive, showed a more modest performance. Logistic Regression, a simpler model, demonstrated the lowest overall performance.These results indicate that LSTM, a deep learning model, is more capable of capturing complex relationships in the data and detecting early-stage chronic diseases compared to traditional machine learning models.

Comparative Study

The results from this study demonstrate the power of deep learning models, particularly LSTM networks, in predicting early-stage chronic diseases. In this section, we compare the performance of the LSTM model with other models commonly used in healthcare prediction tasks, including traditional machine learning algorithms such as Random Forest, Gradient Boosting Machine (GBM), and Logistic Regression, as well as the Feedforward Neural Network (FNN).

LSTM vs. Traditional Machine Learning Models

In our comparative analysis, the LSTM model consistently outperformed traditional machine learning models like Random Forest, Gradient Boosting, and Logistic Regression. One of the key advantages of LSTM networks is their ability to capture long-term dependencies and complex patterns in sequential data, which are common in medical datasets. Early-stage chronic diseases often show gradual onset and subtle patterns that may not be easily captured by more simplistic models.

Random Forest and Gradient Boosting Machines performed better than Logistic Regression but still could not match the LSTM model's ability to discern these complex patterns. While these ensemble models handle non-linear relationships better than traditional linear models like Logistic Regression, they do not possess the temporal depth and sequential learning capabilities of LSTM networks. Random Forest and GBM also rely heavily on feature engineering and can miss subtle interactions between features that LSTM models, with their deep layers, can inherently capture.

Logistic Regression, being a linear model, was the least effective for this problem. It struggled to capture the non-linear relationships inherent in medical data, particularly the complex interdependencies between patient demographics, medical history, and clinical measurements, leading to poorer performance in terms of both recall and accuracy.

LSTM vs. Feedforward Neural Networks

The Feedforward Neural Network (FNN), another deep learning model, performed relatively well but was outpaced by LSTM. Both models are capable of capturing non-linear relationships, but LSTM's architecture is designed specifically to handle sequences and long-term dependencies, which are crucial when predicting early-stage chronic diseases. While FNN works well for static data and does not take into account temporal dependencies, LSTM leverages its ability to "remember" past data points, allowing it to capture trends and interactions in medical data over time.

One limitation of FNN is that it treats each feature independently and does not have the ability to maintain context over time, which is a critical component when dealing with patient medical histories and disease progression. LSTM, by contrast, is structured to handle such sequential dependencies, making it more suitable for tasks involving time-series or sequential data, such as chronic disease prediction, where the disease progression is often gradual and time-dependent.

Real-World Use and Implications

The performance of LSTM in predicting early-stage chronic diseases has important real-world implications, especially in healthcare. Early detection of chronic diseases such as diabetes, cardiovascular diseases, and respiratory conditions is critical to improving patient outcomes and reducing healthcare costs. These diseases often present with subtle symptoms in their early stages, making them difficult to detect without accurate predictive models.

In clinical settings, early diagnosis allows healthcare providers to intervene before the disease progresses, potentially preventing serious complications such as heart attacks, strokes, or organ failure. With the increasing availability of electronic health records (EHR) and wearable health devices that continuously monitor patient health data, LSTM-based models could be used to monitor patients over time, providing real-time risk assessments for early-stage diseases.

For example, in a healthcare system, an LSTM model could analyze a patient's medical history, including past diagnoses, blood test results, and demographic information, to predict the likelihood of developing chronic conditions. This model could be integrated into an AI-powered decision support system that assists doctors in making early diagnoses, offering personalized treatment plans, and recommending lifestyle changes to patients at risk.

Moreover, chronic disease prediction models could be used in telemedicine applications. In remote areas or among elderly populations, where frequent visits to healthcare facilities might be challenging, AI-powered prediction systems can be deployed on mobile devices, helping doctors remotely monitor and assess the risk of chronic diseases. These systems could generate alerts for physicians when a patient is at high risk, enabling proactive interventions even before symptoms become evident.

Additionally, such AI models have significant applications in personalized medicine, where predictions are made based on a combination of personal health data and genetic factors. The integration of AI models like LSTM in these contexts can revolutionize the way healthcare providers identify at-risk individuals and offer timely preventive care.

Limitations and Future Directions

While the results demonstrate the potential of LSTM in predicting early-stage chronic diseases, there are still limitations that need to be addressed. One major limitation is the availability of high-quality, labeled healthcare data. Healthcare data often suffer from issues such as missing values, noise, and imbalanced classes, which can impact the performance of predictive models. Moreover, the black-box nature of deep learning models like LSTM poses challenges in interpretability, making it difficult to understand how the model arrives at specific predictions. This lack of transparency could be a barrier to adoption in healthcare settings where interpretability is crucial for clinical decision-making.

Furthermore, the generalization of the LSTM model across diverse patient populations and healthcare systems remains an open challenge. A model trained on one population might not perform as well on another, especially when there are variations in healthcare practices, patient demographics, and medical data quality. Future work could explore the use of transfer learning, where a pre-trained model is fine-tuned on specific datasets, enabling better generalization across different settings.

In conclusion, deep learning models, particularly LSTM networks, have proven to be highly effective for early-stage chronic disease prediction, outperforming traditional machine learning models. Their ability to capture complex, non-linear relationships in healthcare data, along with their potential for real-time predictions, makes them a powerful tool for early diagnosis and personalized care. As AI continues to evolve and more healthcare data becomes available, these models have the potential to significantly improve the quality of care and outcomes for individuals with chronic diseases.

Conclusion and Discussion

In this study, we explored the application of deep learning models, specifically Long Short-Term Memory (LSTM) networks, in predicting the early stages of chronic diseases. The results demonstrate that deep learning models, particularly LSTM, outperform traditional machine learning models such as Random Forest, Gradient Boosting Machines (GBM), and Logistic Regression in terms of accuracy, precision, recall, F1-score, and AUC. The LSTM model's ability to capture long-term dependencies and complex relationships in sequential data makes it an ideal choice for predicting chronic diseases, where disease progression is often gradual and time dependent.

The LSTM model consistently demonstrated superior performance across all evaluation metrics, with the highest accuracy of 88.7%, precision of 85.5%, recall of 86.3%, F1-score of 85.9%, and AUC of 0.92. These results show that the LSTM model can effectively handle the complexity of medical datasets, which often contain subtle and non-linear relationships between features. By leveraging its ability to learn from historical data and detect long-term patterns, LSTM proved to be particularly valuable in early-stage chronic disease prediction, where capturing these patterns is crucial for timely diagnosis and intervention.

While traditional models like Random Forest and GBM showed strong performance, they were still outperformed by LSTM in handling the complexity of the medical data. These models, while effective at capturing non-linear relationships, lack the sequential learning capabilities of LSTM. On the other hand, Logistic Regression, being a linear model, performed the worst, as it failed to capture the complex interactions and non-linearities present in chronic disease data.

The comparative study also highlighted that LSTM models have a significant advantage in real-world applications, where medical data is often dynamic and includes a range of complex factors such as patient demographics, medical history, and clinical measurements. Traditional models, while useful for certain tasks, often fail to capture the temporal dynamics of disease progression. This is particularly important in the healthcare sector, where timely intervention based on early-stage disease predictions can make a substantial difference in patient outcomes.

Limitations and Challenges

Despite the promising results, several challenges remain in applying LSTM models for chronic disease prediction in real-world settings. One of the key challenges is the availability of high-quality data. While datasets used in this study were publicly available, real-world healthcare data can often be incomplete, noisy, or imbalanced. Incomplete records, missing values, and class imbalances can degrade the performance of deep learning models. Additionally, patient data privacy and regulatory constraints (e.g., HIPAA compliance in the U.S.) can limit the ability to access and utilize large-scale datasets for training.

Another significant limitation is the interpretability of deep learning models. Although LSTM networks are powerful tools for prediction, they function as black boxes, making it difficult to understand how they arrive at specific predictions. In healthcare, where understanding the rationale behind a diagnosis is critical for medical decision-making, the lack of interpretability can pose a barrier to widespread adoption. To address this, future research should focus on improving the explainability of deep learning models, such as using techniques like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) to provide transparent and interpretable results.

Furthermore, while the LSTM model demonstrated superior performance in this study, the generalization of these models across different populations and healthcare systems remains an open question. The model trained on one dataset may not perform equally well on another dataset due to differences in data distribution, patient demographics, and healthcare practices. To address this, techniques like transfer learning or fine-tuning pre-trained models on new datasets could improve the adaptability and generalizability of the model.

Future Directions

The promising results of this study suggest several future directions for improving early-stage chronic disease prediction using deep learning. One area of focus is multi-modal data integration, where models can leverage different types of data, such as genetic data, lifestyle data (e.g., physical activity, diet), and real-time data from wearable devices. Combining these different data sources with traditional clinical data can enhance the predictive accuracy of the models and provide a more holistic view of the patient's health. Moreover, future research can explore hybrid models that combine LSTM with other machine learning algorithms, such as Random Forest or support vector machines (SVM), to further improve predictive performance. Hybrid models have been shown to leverage the strengths of multiple algorithms and might provide better results, particularly in complex healthcare tasks.Finally, as the field of personalized medicine continues to evolve, deep learning models like LSTM could play a pivotal role in creating individualized treatment plans. By accurately predicting which patients are at risk of developing chronic diseases, healthcare systems can tailor preventive measures to each patient's unique health profile, optimizing resource allocation and improving long-term health outcomes.

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