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A Deep Learning Approach for Predicting Hospital Length of Stay for People with Diabetes using Electronic Health Records (EHRs)

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Abstract

Diabetes, which substantially affects the people lives as well as the healthcare systems worldwide, has become the primary area of concern. The purpose of this study is to predict the length of hospital stay among diabetic patients using machine learning (ML), deep learning (DL), along with electronic health record (EHR) data. This work evaluated several models: XGBoost, Random Forest, Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network with LSTM (RNN-LSTM), and an ensemble model combining GAT and CNN in terms of performance metrics used, such as MAE, MSE, and R^2. Among all the models tested, MLP using the top 20 features performed the best, recording an MAE of 0.37 and an R^2 of 0.62. The model emphasized certain critical aspects concerning feature selection and dimensionality reduction, which enhanced the algorithm's accuracy, especially in cases with numerous redundant or verbose variables. More generally, these findings point to the potential that predictive modeling and artificial intelligence have in optimizing the allocation of hospital resources, reducing the costs of health care, and improving patient outcomes, thereby paving the way forward in the development of some clinical decision support tools to manage inpatient diabetic care.

Keywords: *Length of Stay (LOS), Diabetes, Machine Learning, Deep Learning, Feature Engineering, Hospital Prediction.*

1 Introduction

Diabetes has been one of the major chronic disorders with a hyperglycemic state that occurs due to either insufficient insulin or no insulin to utilize. Therefore, economic and health burdens worldwide are substantial, with an estimate of $966 billion expended on this condition in 2021, including medication expenses, hospital admissions, visitation expenses with a doctor, and managing complications [1]. It ranks among the top killers today, claiming more than a million mortalities per year, as well as drastically increasing the likelihood of severe consequences such as cardiovascular diseases, renal failures, neuropathy, blindness, and limb amputations; the latter ailments substantially affect the quality of life and economic productivity [2]. Effective management of such chronic illness requires constant medical care and regular hospital visits, inadvertently leading to hospital overcrowding and the prevalence of diabetic emergencies, for cases such as ketoacidosis and hypoglycemia [3]. It is highly recommended that health systems adopt multi-faceted strategic approaches to concentrate on prevention, early detection, and management. The most crucial advances in artificial intelligence and digital health systems can enhance the accuracy of diagnosis, provide personalized treatment methods for patients, and make it possible to effectively manage patient health while maintaining distance [4].

Due to the digitalization of patient information, Electronic Health Records (EHRs) have brought a substantial revolution in providing healthcare services that have improved methods of communication and data accuracy, leading to an enhanced overall efficiency of clinical practice [5]. In health promotion activities, they represent a crucial path to support best available evidence through the promotion of health trend analysis, monitoring outcomes, and applying interventions that are specifically targeted [6]. When connected to big data analytics, EHRs allow for predictive modeling, early diagnosis, and application-tailored, precision-based approaches to healthcare [7].

It is important for healthcare management to be able to predict the hospital LOS accurately, as such prediction aids in optimizing resource utilization through streamlining beds, managing staff, and partly guiding discharge planning and thereafter the post-acute care processes [8]. Length of stay prolongation is a common complication encountered in diabetic inpatients and is determined by several factors, such as general health status, comorbidities, poor glycemic control, foot infections, and cardiovascular diseases. Furthermore, healthcare accessibility and support networks, two pillars aside from giving healthcare concerns social determinants of health, impact the LOS. Therefore, scientific LOS forecasting is essential in diabetic patients, given its influence on the quality of operation and clinical outcomes, a reduction in readmission rates, ways to reduce financial distractions for the huge healthcare burden, and the need for good care quality overall in this hospitalized population [9].

Predictive analytics for hospital length of stay (LOS) could be achieved with good accuracy by using patient demographics, comorbidities, laboratory tests, and electronic health records with the help of recent advances in artificial intelligence (AI), machine learning (ML), and deep learning (DL) technologies [10]. DL models, specifically, are able to make real-time predictions, thus improving hospital resource planning, in addition to their ability to capture complex nonlinear relationships among patient data. The purpose of this research is to build an accurate deep-learning-based predictive model concerning LOS among diabetic patients by merging and simplifying data sources, highlighting important predictive items, and comparing the DL models' performance with that of classical ML methods.

The remainder of this paper is organized as follows: Section 2 presents a review of related literature; Section 3 describes the methodology employed in this study; Section 4 discusses the experimental results and findings; and Section 5 concludes the paper with recommendations for future research.

2 Related Work

Recent investigations have performed geophysical studies on identifying the causative factors behind hospital length of stay (LOS) in different patients and clinical contexts to enhance resource utilization and operational efficiency. A randomized clinical trial in patients with opioid use disorder (OUD) evaluated the co-located bridge clinic and interestingly showed no differences in LOS medians but significantly improved post-discharge outcomes, which included treatment adherence and care continuum. These results emphasize the severity of OUD, treatment adherence, and access to transitional services among differentiating factors that are linked with LOS [11]. A previous study suggested that ML models were satisfactorily effective in LOS prediction vis-a-vis pediatric hospital admissions in Brazil, with the Random Forest model yielding an R^2 value of 65.67% and an absolute mean error of 3.51 days, which signified the importance of the prediction of demographic, clinical, and treatment-related variables.

Personalized ML models for LOS prediction have been improved with the advent of larger datasets. The New York SPARCS dataset provided confirmation of linear regression as the best predictive tool among newborns ($R^2 = 0.82$) and CatBoost for non-newborns ($R^2 = 0.43$), supporting improved capacity planning and cost optimization. Various factors of prolonged LOS in an ortho-surgery cohort were preoperative hemoglobin, BMI, age, height, and comorbidities, for the best predictive performance from K-Nearest Neighbors (AUROC = 0.8191), along with help from a web-based preoperative risk assessment tool [12]. In the field of orthopedics, several predictors might be associated with age, height, possible comorbidities, preoperative hemoglobin, BMI—most important among the predictors of increased LOS following the surgery for posterior spinal deformity—using the method of K-Nearest Neighbors that gave top-scoring performance value (AUROC = 0.8191), and an online preoperative risk assessment tool [12]. Additionally, analysis of the ACS-NSQIP dataset [13] indicated that postoperative complications like extended mechanical ventilation, wound dehiscence, and renal failure contribute significantly to raising LOS, thus underscoring the necessity for recourse to data-driven decision-making in terms of planning for surgery, managing discharge, and allocating resources.

Many traditional LOS predictions were based on basic statistical procedures like linear regression, Cox regression, survival analysis, and others of that sort. These strategies do not effectively handle patient heterogeneity, dissociating high-dimensional and unstructured datasets from practical use: hence, they are less likely to improve predictability, thus limiting the help they can currently offer to clinicians dealing with heterogeneous data in the emergency room, in or during orthopedic surgery, or the management of ICU patients [14]. Advanced ML and DL techniques have emerged as a result of data complexity and volume. Some deep-learning models, like CNNs, RNNs, LSTMs, and hybrid GAOCNN, significantly improve LOS and readmission predictions by pulling the temporal and unstructured data into meaning. These models have performed better than the other frameworks and show AUCs approaching 0.95 and accuracies approaching 92% [15][16].

DL models like LoSNet are also an embodiment that denotes the full potential of AI, specifically in LOS models. LoSNet, a disease-specific DL framework, was put to work on both training and validation data from a sample of 318,000 patient records across eleven LOS classes and compared against traditional ML algorithms such as Random Forest, Decision Tree, Logistic Regression, and the Naïve Bayes on COVID-19 datasets. The model achieves a cross-entropy loss of 1.531 and an accuracy of 0.408 for COVID-19 patients. However, a few constraints surface, which might limit its effectiveness--greatly skewed numbers in some classes, the absence of any method regarding feature importance, and the like [17].

Based on the above, these studies show a significant shift from traditional statistical methods to AI-driven predictive analytics, which greatly enhance forecasting length of stay, patient care, and hospital resource allocation. Despite this, challenges like the quality of data, real-time bedside integration, transparency in methodology, and applicability to diverse populations are significant. This research thoroughly examined various DL models, including MLP, CNN, and RNN-LSTM, as well as Ensemble approaches like GAT+CNN, to predict diabetic cases based on electronic health record data encompassing demographics, lab results, diagnoses, and treatments [18].

3 Methodology

This research sets a robust multi-stage approach for predicting the Length of Stay (LoS) with diabetic patients at hospitals employing a variety of ML and DL techniques. The proposed methodology deals explicitly with addressing the complexity and clinical data heterogeneity by equally emphasizing reproducibility, reliability, and interpretability at each stage of model development. The study is structured into three main stages:

1. Data Preprocessing is conducted using diverse approaches since the dataset comes with both numerical and categorical attributes. The missing values for numerical characteristics are filled by means of median imputation, whereas for categorical features, imputing is done by applying mode. After that, all the numerical columns are transformed with the help of z-score normalization through the StandardScaler method which results in features with zero mean and unit variance that, in turn, allows the convergence of many of the learning algorithms. The mapping of the categorical attributes depends on the cardinality of the features. Low cardinality features are changed by label encoding, on the contrary, for high-cardinality features, the one-hot encoding is preferred for preserving the categorical distinctions.
2. Feature Engineering and Selection – Feature engineering techniques will be employed to create additional informative variables, including *estimated_total_stay_days*, *total_previous_visits* (aggregated from outpatient, inpatient, and emergency encounters), *age_gender_interaction*, and *num_active_meds*. These engineered features are expected to improve the model's capacity to capture latent patterns associated with hospital stay duration.
3. Model Development, Testing, and Optimization – The ML and DL models are trained and validated, and then fine-tuned following the evaluation of performance metrics. Ultimately, all guidance and choices regarding actions will be based on the most effective practices in healthcare analytics. Our focus is on scale, robustness, and clinical treatment.

In order to carry out the study, a publicly accessible dataset from the UCI Machine Learning Repository, with the electronic health records of diabetic patients from 130 hospitals in the United States and data collected between 1999 and 2008 [19] was used. The dataset provides data for 101,766 patients and includes 50 features that cover demographics, clinics, administrations, and treatments, making it perfectly ideal for predicting LOS. Specific aspects of the dataset include:

- Patient characteristics: age, gender, race.
- Admission details: admission type, source, and discharge disposition.
- Clinical measurements: number of lab procedures, medications, diagnoses, and blood glucose tests.
- Medical services utilized in the recent past- outpatient, inpatient, and emergency.
- Therapeutic interventions specific to diabetes- additions to medication; insulin therapy.

The primary outcome variable, length of hospital stay, is captured from the "time in hospital" feature and treated as a continuous variable. Normalization of skewed distributions was performed as necessary.

A comprehensive model approach was adopted, integrating DL and classical ML techniques. Among the DL models considered are CNNs, MLPs, RNN-LSTMs, and ANNs (fully connected artificial neural networks). Graph-based models, particularly GNNs with attention layers, allow for dependencies among data in the context of a patient. Classical ML models (Random Forest and XGBoost) serve as baseline models. Ensemble frameworks, such as hybrid methods of combining CNN and GAT predictions, help to leverage the strengths of both.

For testing and validation, models are trained in an 80:20 training-testing approach, using the Adam optimizer along with a Mean Squared Error (MSE). Techniques such as early stopping and changing learning rates are used to prevent overfitting. These models are validated using performance metrics such as MAE, R^2, and MSE, along with visual representations like learning curves and residual plots.

An analysis of the importance of the features is based on permutation importance in DL models and on gain-based scores in tree-based models. Moreover, selecting the leading 20 features to decrease dimensionality offers classifiers a promising and balanced performance boost.

Another ensemble strategy, late fusion, combines CNN GAT predictions to capture both spatial and relational patterns in the medical data. Hyperparameter tuning is done for tuning the XGBoost method. Optuna is used for Bayesian optimization, while hyperparameters that include the learning rates, representation depth, regularization, and subsampling mechanism are fine-tuned in order to maximize the predictive performance.

4 Results, Analysis, and Discussions

A variety of ML and DL architectures have been evaluated to predict the hospital length of stay (LOS) of patients with diabetes. Standard regression metrics, like Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2), were used in the assessment to ascertain levels of predictive performance and the explained variance. The methods used, in combination with the 80:20 training and test set split, were aimed at ensuring a reliable evaluation and provided further means for validation by early stopping techniques, the use of k-fold cross-validation, among others, to prevent overfitting, and increase generalizability. From these performed metrics alone, a descriptive comparison of classical ML models, DL networks, and ensemble-based hybrid approaches can be accomplished. Each one is good in its own unique way in capturing complex and heterogeneous patterns present in electronic health record (EHR) data.

4.1 Convolutional Neural Network (CNN)

The architecture of the model had several convolutional layers with filter sizes that decreased gradually (256 → 128 → 64). Each layer was followed by batch normalization and LeakyReLU activation to improve training stability. To combat overfitting, dropout layers were also introduced in between. After the convolutional phase, there were dense layers that were fully connected, consisting of a 128-unit ReLU and a linear output unit for regression as the last layer. This setup produced MAE = 0.45, MSE = 0.41, and $R^2 = 0.58$ as evaluation metrics.

Looking at the learning curve, the CNN exhibits a stable convergence and minimal overfitting without any large exceptions. Applying residual error analysis, a good approximation of unbiased error data is observed (Figs. 4.1–4.2).

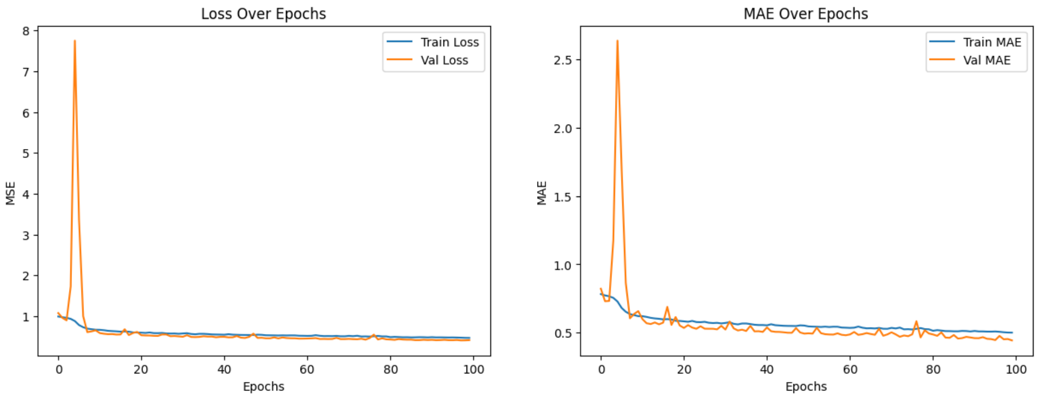

Figure 4.1: *Model Learning Curves over Epochs.*

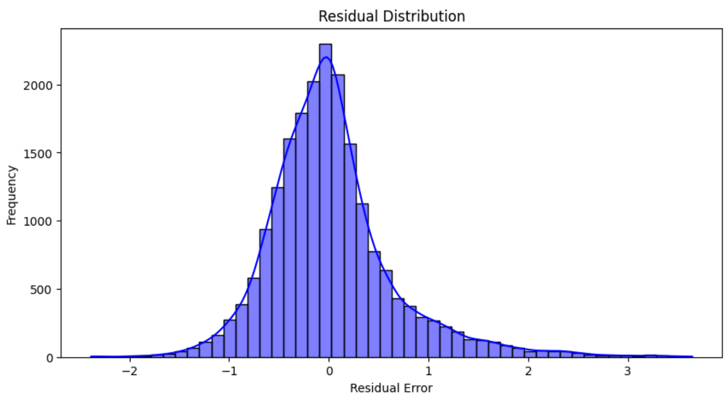

Figure 4.2: *Residual Error Distribution.*

4.2 Multilayer Perceptron (MLP)

In terms of individual models, the deep MLP essentially containing four dense layers (512 → 256→ 128→ 64) had the highest predictive accuracy with MAE = 0.38, MSE = 0.41, and R² = 0.62. The learning curves clearly show the occurrence of capacity to generalize (Figure 4.3), and permutation importance ensured that *estimated _total_stay_days* and *number_inpatient* were significant predictors (Figure 4.4), which is in line with our clinical intuition. Limiting model training to the top 20 variables slightly confirms the value of a decrease in learning capacity while maintaining a balance between performance and computational time (MAE = 0.37, MSE = 0.40, R² = 0.62; Figure 4.5).

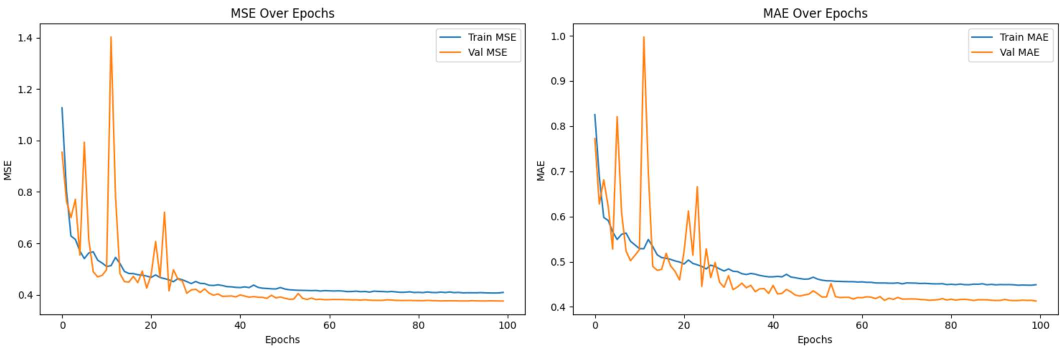

Figure 4.3: *MSE and MAE Learning Cur*

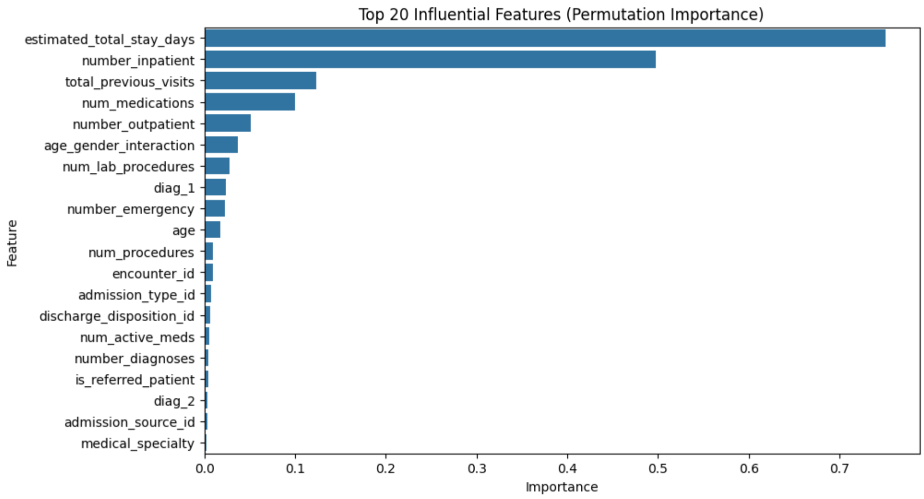

Figure 4.4: *Top 20 Features Ranked by Permutation Importance.*

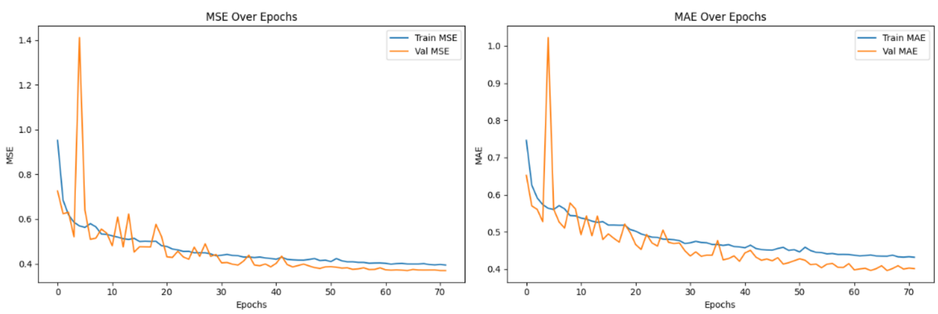

Figure 4.5: *Training and Validation Loss Curves for Optimized MLP Model.*

4.3 Recurrent Neural Network – LSTM

An RNN LSTM model trained on the whole set of featurized time-series data, converted to sequence mode, was effectively able to capture temporal patterns with MAE = 0.42, MSE = 0.46, and R^2 = 0.57. The learning curves also looked stable, with very small fluctuations (Figure 4.6).

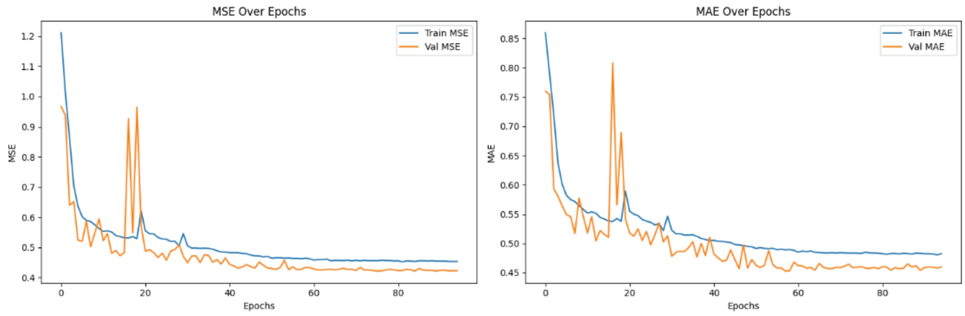

Figure 4.6: *MSE and MAE over training epochs for the RNN-LSTM model.*

4.4 Graph Neural Network (GNN)

To further enhance the regression performance in predicting the hospital length of stay, an improved Graph Neural Network (GNN) model was developed using the PyTorch Geometric framework. This model employed Graph Attention Layers (GATConv), batch normalization, dropout regularization, and a fully connected regression head. The graph was constructed using a k-nearest neighbors (k-NN) approach based on PCA-reduced features. After 300 epochs, the model achieved MAE = 0.36, MSE = 0.20, and R^2 = 0.27. Residuals approximated a normal distribution centered around zero, indicating largely unbiased predictions (Figure 4.7).

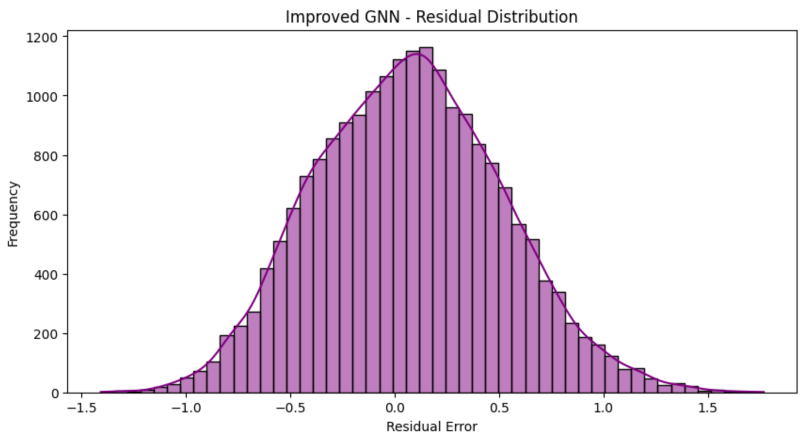

Figure 4.7: *Residual Error Distribution of GNN.*

4.5 GAT+CNN Ensemble

The combined forecasting of CNN and GAT gave a much more impressive performance than did the individual methods, boasting MAE (ten-fold CV) = 0.34, MSE = 0.18, and R^2 = 0.35. Residuals were confirmed to show normal distribution, which is why the residuals, the permutation analysis identified *num_medications*, *num_lab_procedures*, and *discharge_disposition_id* as key contributing predictors. As it subsequently decreases to the top 12 features ensemble, this performance edge was slightly increased with a further improvement in efficiency (MAE = 0.33, MSE = 0.17, R^2 = 0.36) as shown in Figures 4.8 and 4.9.

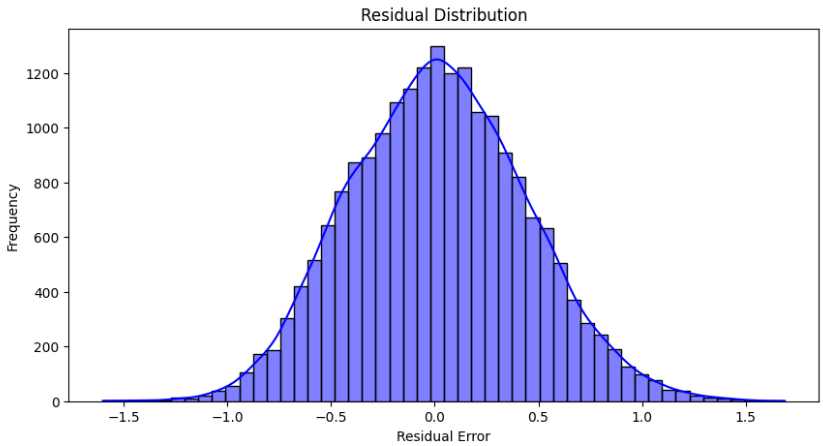

Figure 4.8: *Residual Error Distribution of GAT+CNN Ensemble.*

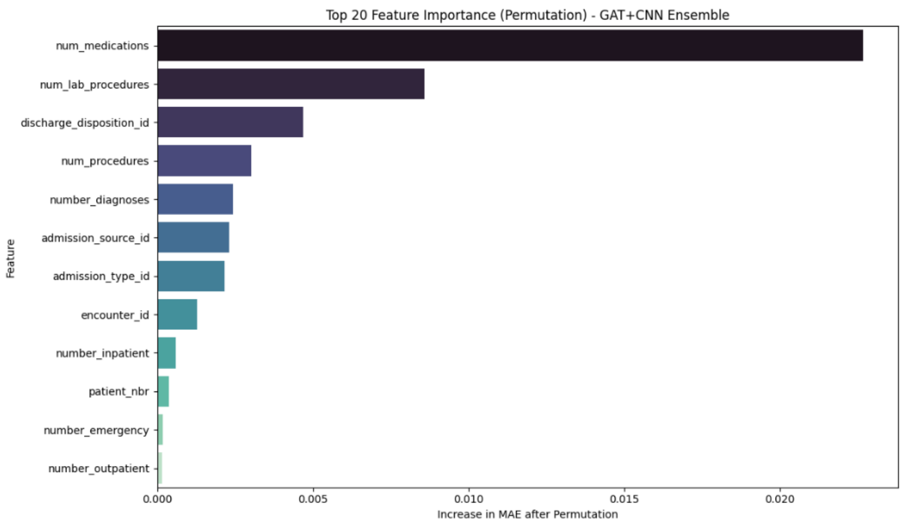

Figure 4.9: *Top 20 Features Ranked by Permutation Importance.*

4.6 Artificial Neural Network (ANN)

A robust ANN model was developed and tested, which was built on a more sophisticated architecture. Improvements to the architecture included adding dropout layers to prevent overfitting, implementing batch normalization to stabilize the gradient flow by managing internal covariate shifts, and increasing the depth of networks to model complex nonlinear relationships better. Post-training, the model was qualitatively assessed and visually evaluated for the extent to which it could predict the length of stay in terms of diabetes for hospital patients. The model featured satisfactory but moderate model performance (MAE = 0.58, MSE = 0.59, R^2 = 0.40). The error residuals were symmetric and unbiased in distribution, as shown in Figure 4.10.

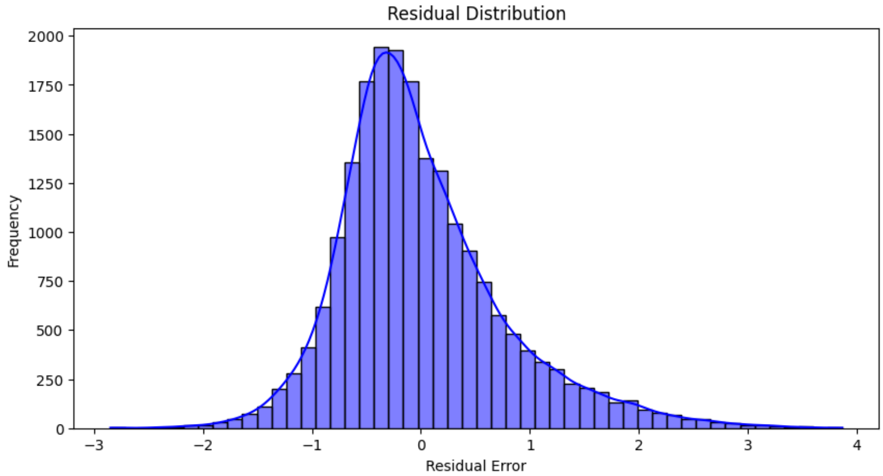

Figure 4.10: *Residual Error Distribution of ANN Predictions.*

4.7 XGBoost

During this testing process, the XGBoost regression model is obtained following hyper-parameter tuning using the Optuna framework. The XGBoost algorithm for gradient boosting was chosen owing to its ability to fit complex data structures and nonlinear relationships. Once the parameters were adapted using Optuna, the model's best performance was achieved with MAE = 0.52, MSE = 0.48, and R^2 = 0.50. The feature analysis disclosed in Figure 4.11 revealed that the more critical features were *num_medications* and *discharge_disposition_id*, aligning with medical intuition expectations.

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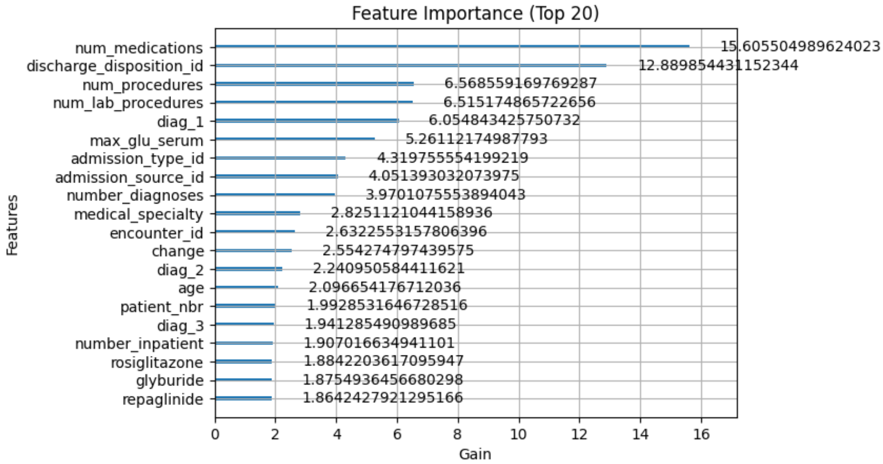

Figure 4.11: *Feature Importance (Top 20).*

4.8 Random Forest

The Random Forest Regressor was implemented here to determine the number of days the diabetic patients spent in the hospital. The baseline RF model (n_estimators=200, max_depth=10), however, presented weaker performance (MAE=1.71, MSE=1.13, R^2=0.42). But the residual patterns showed reasonable predictive stability (Figure 4.12).

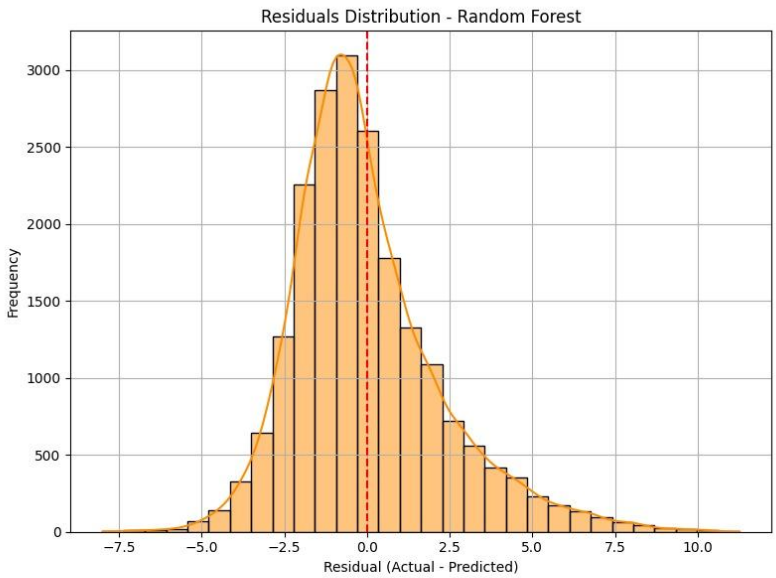

Figure 4.12: *Residuals Distribution - Random Forest.*

4.9 Comparative Model Performance

Presented in Table 4.1 is a comparative evaluation of all models taking into account MAE, MSE, and R^2. The GAT+CNN ensemble exhibited the lowest MAE, whereas the highest R^2 (0.62) was shown by the MLP trained on the top 20 features of the model. Thus, the CNN and RNN-LSTM models provide competitive performance, while Random Forest and ANN have underperformed relative to optimized DL architectures.

Table 4.1: *Overall Performance Comparison Across All Models.*

Model	MAE	MSE	R^2 Score
GAT + CNN Ensemble	0.34	0.18	0.35
MLP (Top 20 Features)	0.37	0.40	0.62
GNN	0.36	0.20	0.27
MLP (All Features)	0.38	0.41	0.62
CNN	0.41	0.45	0.58
RNN-LSTM	0.42	0.46	0.57
XGBoost	0.52	0.48	0.50
Random Forest	1.71	1.13	0.42
ANN	0.58	0.59	0.40

4.10 Effect of Feature Selection

Once the dimensionality was decreased, the Ensemble of GAT and CNN models became advanced enough to be retrained and tested for their prediction capabilities. Therefore, permutation importance was employed to identify the top 20 features for using retrained weights in the Ensemble model. In this category, feature selection not only preserved the performance but also enhanced computational efficiency without severely adverse impacts on the precision of the data. For instance, the GAT+CNN ensemble reduced MAE to 0.33 and MSE to 0.17, while increasing R^2 to 0.36, while MLP with top features reduced MAE to 0.37 and maintained $R^2 = 0.62$, as shown in Table 4.2.

Table 4.2: *Comparison of Models with and without Top Feature Selection.*

Model	Features Used	MAE	MSE	R^2 Score
MLP	All Features	0.38	0.41	0.62
MLP	Top 20 Features	0.37	0.40	0.62
GAT + CNN Ensemble	All Features	0.34	0.18	0.35
GAT + CNN Ensemble	Top 20 Features	0.33	0.17	0.36

4.11 Discussion and Limitations

This research has a number of limitations. The models were developed on a U.S.-based EHR dataset (1999-2008) and the retrospective nature of the dataset may limit its application to current clinical practices. The preprocessing step might not totally eliminate the bias and the problem of EHR data notably missing data and coding inconsistency, might still introduce some bias. The length of stay outcome was treated as a continuous variable without distinguishing between censored admissions and post-discharge outcomes. Moreover, usage of DL and ensemble models requires more computational power and less interpretable, which might consequently result in not being immediately accepted in clinics. Finally, the models have not undergone external validation using independent datasets, which restricts their range of use.

It is worth noting that an MAE of less than one day provides clinically significant precision for early risk classification and hospital management instead of precise discharge timing. The model can be used by the clinician at admission to detect the patients who are going to have longer or shorter hospital stays, thus making it possible to intervene in time, coordinate discharge in advance, and allocate resources efficiently. If such predictions are made on a large scale, they will improve bed management and patient flow while supporting and not substituting clinical judgment.

5 Conclusion

This study's results indicate that the application of fitting model architectures and significant features could significantly improve the prediction of hospital length of stay (LOS) in diabetic patients. The MLP model which was trained on the entire feature set had the best performance, thus beating all other DL models that were tested in this research. More so, by using the top 20 features which were chosen according to their permutation importance, the generalization of the MLP model was improved, thus proving the worth of feature-relevance-guided dimensionality reduction. All in all, these findings suggest that DL models, along with proper feature engineering and ensembling, deliver a robust, interpretable, and clinically relevant approach for LOS prediction which can greatly aid in the management of hospital resources and improving patient care outcomes.

Longitudinal EHR data analysis will be the subject of future work to gather more information about temporal patterns that affect hospital length of stay. The utilization of multi-center and more recent datasets will lead to an increase in the generalizability of models. Explainable AI methods will be incorporated to treat clinical interpretability. Last, but not least, the real-time deployment of clinical decision support systems will be researched.

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