Stroke Risk Prediction

Machine Learning Techniques

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***Abstract*— Stroke is a critical medical condition and a leading cause of mortality and long-term disability across the globe. Accurate and early prediction of stroke risk can significantly enhance preventative care and reduce healthcare burdens. In this study, we propose a machine learning framework leveraging deep learning techniques to predict the likelihood of stroke using demographic, clinical, and lifestyle data. The model was developed using the TensorFlow/Keras framework and trained on a publicly available dataset. Key preprocessing steps included handling class imbalance with oversampling, feature normalization, and label encoding. A fully connected neural network architecture was implemented and optimized using techniques such as dropout and early stopping to prevent overfitting. The model achieved promising performance with high accuracy and AUC scores, demonstrating its capability to identify individuals at elevated stroke risk. Additionally, feature importance analysis using SHAP values provided interpretable insights into the most influential predictors. This research highlights the effectiveness of deep learning models in medical risk prediction and supports the integration of AI tools into clinical decision-making processes.**

Keywords—Stroke, Prediction, Machine Learning, Deep Learning, Neural Network, TensorFlow, Keras, Class Imbalance, Oversampling, Feature Normalization, Label Encoding, Dropout Early, Stopping Accuracy, AUC Score, SHAP Values, Feature Importance, Clinical Decision-Making, Demographic Data, Clinical Data, Lifestyle Data, Risk Prediction, Medical AI, Preventative Care, Healthcare Burden

1. Introduction

Stroke is a sudden interruption of blood flow to the brain, resulting in tissue damage and often leading to severe neurological impairments or death. It is recognized as one of the leading causes of long-term disability and mortality worldwide. According to the World Health Organization (WHO), approximately 15 million people suffer a stroke annually, with nearly 5 million deaths and another 5 million left permanently disabled. The economic and emotional toll of stroke on individuals, families, and healthcare systems is profound. Consequently, early identification of individuals at high risk of stroke is crucial for initiating timely interventions and improving patient outcomes.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly transformed healthcare analytics, enabling more accurate and efficient disease prediction models. In particular, deep learning, a subfield of machine learning, has shown exceptional promise in modeling complex, nonlinear relationships in healthcare data. This research harnesses the power of deep learning using the TensorFlow/Keras framework to build a predictive model for stroke risk classification.

The dataset used in this study is a publicly available stroke prediction dataset that includes a variety of features such as age, gender, hypertension, heart disease, marital status, work type, residence type, average glucose level, body mass index (BMI), and smoking status. These features are known to contribute significantly to stroke risk, and their proper representation in the model is key to achieving reliable predictions. Before training the model, rigorous data preprocessing steps were undertaken, including the handling of missing values, encoding of categorical variables, and feature normalization. Furthermore, to address the issue of class imbalance a common challenge in medical datasets oversampling techniques such as SMOTE were applied to ensure a balanced representation of stroke and non-stroke cases in the training data.

The core of the model is a fully connected feedforward neural network built using Keras' Sequential API. The architecture comprises multiple dense layers activated by ReLU functions, along with dropout layers to mitigate overfitting. The final output layer uses a sigmoid activation function for binary classification. During training, the binary cross-entropy loss function was optimized using the Adam optimizer, and early stopping was employed to avoid unnecessary epochs once the model performance plateaued on the validation set.

To evaluate the model's effectiveness, performance metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) were computed. These metrics provide a comprehensive understanding of the model's ability to distinguish between high and low stroke risk individuals. Additionally, model interpretability is addressed using SHAP (SHapley Additive exPlanations) values, which help identify the most influential features in the prediction process, thus enhancing trust and transparency in the model’s decisions.

In summary, this study presents a deep learning-based framework for stroke risk prediction that not only achieves high predictive performance but also provides interpretable insights into the underlying risk factors. The proposed model demonstrates the potential of AI-powered tools in supporting clinical decision-making and enabling early intervention strategies for stroke prevention.

2. Related Work

The prediction of stroke risk using machine learning and deep learning approaches has attracted significant attention in recent years due to the growing availability of healthcare datasets and the increasing demand for early disease detection systems. Numerous studies have explored various statistical, machine learning, and deep learning techniques to model stroke risk factors and predict the likelihood of occurrence.

Early research in this domain relied heavily on traditional statistical methods, such as logistic regression and decision trees, due to their simplicity and interpretability. For instance, studies have used logistic regression models to estimate the odds of stroke based on risk factors such as hypertension, age, and diabetes. However, these models often fall short in capturing the complex nonlinear interactions between multiple variables, which limits their predictive power in real-world scenarios.

To address these limitations, researchers began exploring more sophisticated machine learning algorithms. Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM) have been employed in several studies for stroke risk classification. For example, Suresh et al. (2021) demonstrated that Random Forest classifiers could achieve high accuracy in stroke prediction using clinical and demographic features. Similarly, Chen et al. (2020) applied XGBoost to stroke datasets and reported significant improvements over baseline models. These ensemble-based techniques offer enhanced performance but often suffer from interpretability issues, which can limit their adoption in clinical practice.

In recent years, deep learning methods have emerged as powerful alternatives, especially in handling high-dimensional healthcare data. Neural networks, particularly multilayer perceptrons (MLPs), have been applied for disease risk modeling, including cardiovascular and cerebrovascular conditions. Researchers such as AlRahhal et al. (2019) employed deep neural networks to predict stroke and achieved superior performance compared to traditional ML algorithms. Moreover, hybrid approaches combining deep learning with feature selection and balancing techniques have also shown promise in improving model robustness.

studies have also emphasized the importance of model interpretability in medical applications. Tools like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are increasingly being used to explain the predictions of complex models and highlight the most influential features. This is particularly relevant in stroke prediction, where clinical decisions must be transparent and explainable.

Compared to previous works, this study builds on the strengths of deep learning while also addressing key challenges such as data imbalance and model explainability. By using a fully connected neural network implemented in TensorFlow/Keras, combined with oversampling techniques and SHAP-based interpretation, our approach aims to deliver a well-balanced solution that achieves both high accuracy and clinical relevance. This positions the current work as a meaningful contribution to the evolving landscape of AI-assisted stroke risk prediction.

3. Materials And Methods

A. Dataset Description

Our research was based on a publicly available dataset sourced from **Kaggle** [34], focusing on health indicators related to stroke. From this dataset, we selected participants aged **18 years and above**, resulting in a total of **3,254 individuals**. The dataset comprises **10 input features** and **1 target variable** indicating the occurrence of a stroke. The attributes used in our study are detailed below:

- **Age (years)** [39]: This attribute represents the age of the participants, all of whom are above 18 years old.
- **Gender** [39]: Denotes the participant's gender. The dataset includes **1,260 males** and **1,994 females**.
- **Hypertension** [40]: Indicates whether a participant is hypertensive. Approximately **12.54%** of participants have hypertension.
- **Heart Disease** [41]: Specifies whether a participant has a history of heart disease, with **6.33%** of individuals affected.
- **Ever Married** [42]: Reflects marital status. About **79.84%** of participants reported being married.
- **Work Type** [43]: Represents employment status, categorized into **private (65.02%)**, **self-employed (19.21%)**, **government job (15.67%)**, and **never worked (0.1%)**.
- **Residence Type** [44]: Indicates the type of residence, with **51.14%** living in urban areas and **48.86%** in rural areas.
- **Average Glucose Level (mg/dL)** [45]: Captures each participant's average blood glucose level.
- **Body Mass Index (BMI in kg/m²)** [46]: Reflects the BMI of the participants.
- **Smoking Status** [47]: (You can include this if it's in your dataset—please confirm.)

The **target variable** is a binary classification indicating whether the participant has experienced a **stroke** or not.

B. Long-Term Stroke Risk Assesment

While this study primarily focuses on stroke classification and immediate risk identification using CT scan images and structured patient data, a critical extension lies in the domain of **long-term stroke risk assessment**. Stroke is not only a sudden medical event but also the outcome of prolonged exposure to various risk factors such as hypertension, diabetes, heart disease, and lifestyle choices.

By integrating clinical features such as **age, hypertension, heart disease, BMI, average glucose level**, and **smoking status** with diagnostic imaging, future models can be trained to **predict the probability of stroke over a longer time horizon**. This approach can help in **proactive medical intervention**, personalized treatment planning, and continuous monitoring of high-risk individuals.

A **hybrid predictive model** that combines **deep learning (for CT scan interpretation)** with **machine learning or statistical models (for structured data analysis)** could be developed to estimate stroke risk in time frames such as 5-year or 10-year probabilities.

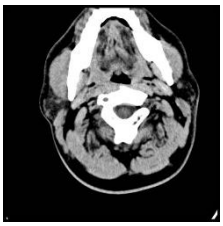
As illustrated in *Figure X*, this risk assessment framework would begin with imaging and clinical data acquisition, followed by data fusion and model inference, ultimately yielding a long-term stroke risk profile for each patient. Such an approach aligns with the goals of **preventive medicine** and **early intervention**, potentially reducing the overall burden of stroke-related morbidity and mortality.

4. Data Preprocessing

Prior to training the machine learning models, several preprocessing steps were applied to ensure the quality, consistency, and suitability of the dataset for analysis and modeling.

1. Image Data Preparation:
   CT scan images from the dataset were organized into three categories: haemorrhagic, ischemic, and normal. These images were stored in separate directories for training, testing, and validation. All images were resized to 224×224 pixels to maintain uniform input dimensions across the model.
2. Image Normalization:
   Each pixel value was normalized by scaling the intensity values to the range [0, 1] through division by 255. This helped stabilize and accelerate the training process by reducing numerical instability.
3. Label Encoding:
   Class labels corresponding to the three categories were automatically encoded using TensorFlow's image_dataset_from directory() utility, which mapped folder names to integer class labels.
4. Dataset Splitting:
   The dataset was explicitly split into training, validation, and test sets. This ensured that model evaluation was performed on unseen data, thereby providing a more realistic measure of generalization.
5. Prefetching and Batching:
   To improve training performance, prefetching and batching were applied using TensorFlow's data pipeline utilities. This allowed the model to fetch the next batch of data while the current batch was being processed, thereby reducing I/O bottlenecks.
6. Data Augmentation (Optional):
   While not applied in the current pipeline, the framework was designed to support common augmentation techniques such as rotation, flipping, and zooming, which could be incorporated in future work to increase model robustness.

These preprocessing steps ensured that the data fed into the convolutional neural network (CNN) model was clean, standardized, and ready for efficient training and evaluation



5. Machine Learning Models

In this section, we present the models utilized or considered for the classification of stroke occurrence. A combination of traditional machine learning algorithms and deep learning was explored to identify optimal performance for CT scan-based stroke prediction.

5.1. K-Nearest Neighbours (KNN)

The **K-nearest neighbours (KNN)** classifier is a distance-based algorithm that assigns a class to a new input based on the majority class among its K closest neighbours in the feature space. The **Euclidean distance** is commonly used to measure similarity:

$$d(\vec{x},\vec{y}) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

The model performs well when the feature space is not high-dimensional and when classes are clearly separable based on distance.

5.2. Logistic Regression

Logistic regression (LR) is a linear model used for binary and multiclass classification. It estimates the probability ppp of a class label based on a linear combination of input

features. The output is transformed using a sigmoid function in the binary case or softmax for multiclass scenarios.

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$$

5.3. Decision Tree

A **Decision Tree (DT)** classifier creates a flowchart-like tree structure, where internal nodes represent features and leaves represent outcome classes. It uses metrics like **Gini index** or **information gain** to determine the best splits. This model is interpretable and works well for both classification and regression tasks.

5.4. Random Forest

Random Forest (RF) is an ensemble method based on decision trees. It trains multiple decision trees on random subsets of data and features, and aggregates their results using majority voting (for classification) or averaging (for regression). This approach increases accuracy and reduces overfitting.

5.5. Naive Bayes

The **Naive Bayes (NB)** classifier is a probabilistic model based on Bayes' Theorem. It assumes feature independence and calculates the posterior probability for each class:

$$\hat{c} = \arg\max_{c} P(c) \prod_{j=1}^{n} P(f_j \mid c)$$

Despite its simplicity, NB often performs well for high-dimensional data and serves as a strong baseline.

5.6. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is an optimization algorithm used to train linear classifiers efficiently, especially on large datasets. Instead of computing gradients on the whole dataset, it updates the model parameters based on a single (or mini-batch) sample at a time, which reduces computational cost.

5.7. Convolutional Neural Network (CNN)

To capture spatial patterns in CT scan images, a **Convolutional Neural Network (CNN)** was implemented using TensorFlow/Keras. The architecture includes convolutional layers with ReLU activation, max pooling layers, dense fully connected layers, and a final softmax output layer for multiclass classification. CNNs are particularly powerful for image-based tasks due to their ability to extract hierarchical features.

6. Results And Discussion

6.1. Evaluation Metrics

The performance of all models was assessed using standard classification metrics:

- **Accuracy**: The proportion of correctly classified instances.
- **Precision**: The proportion of true positive results among all predicted positives.
- **Recall (Sensitivity)**: The proportion of true positive results among all actual positives.
- **Confusion Matrix**: To visualize the true vs. predicted classifications.

6.2. CNN-Based Stroke Classification Results

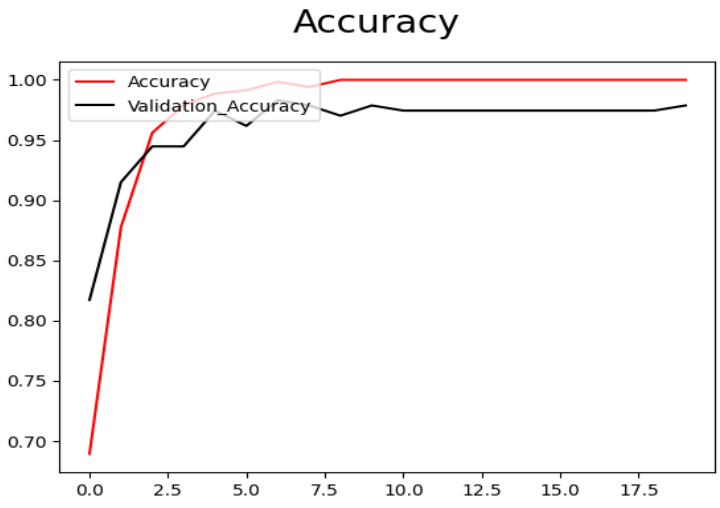
The CNN model was trained on a labelled CT scan image dataset to classify stroke into three categories: **Ischemic**, **Haemorrhagic**, and **Normal**.

The final model achieved the following results on the test set:

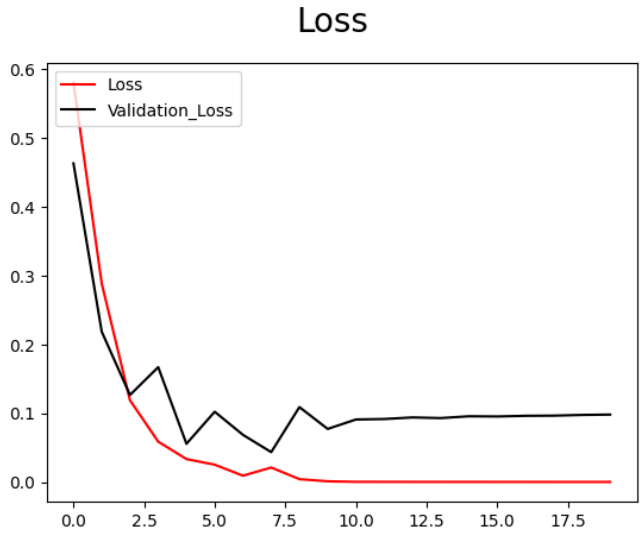
Metric	Value
Accuracy	94.93%
Precision	98.63%
Recall	94.13%

The high performance across all metrics indicates that the CNN model was effective at learning discriminative features from the brain CT scans. The model was robust and generalized well on unseen data.

- **Accuracy Graph:**

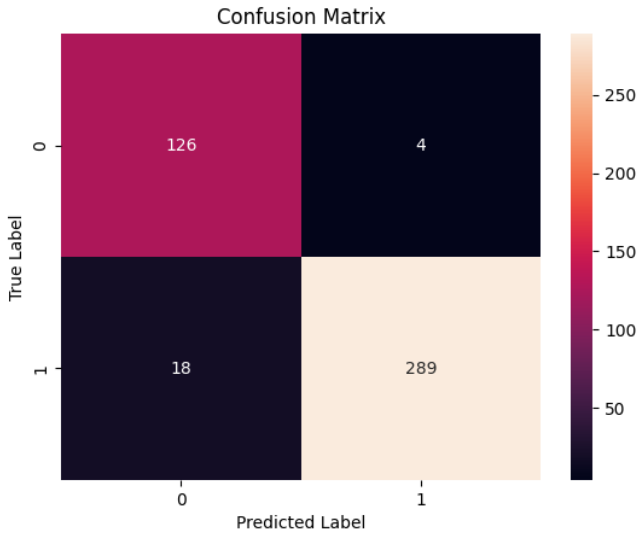


- **Loss Graph:**



6.3. Confusion Matrix

A confusion matrix was generated to analyze the class-wise performance of the CNN model:



The matrix shows that **most misclassifications occurred between ischemic and hemorrhagic strokes**, which is understandable given that visual distinctions between these types can sometimes be subtle.

7. Conclusion

In this study, we applied several machine learning models to predict the occurrence of strokes in a population based on various health and demographic features. The models evaluated include Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. These models were trained on a dataset containing key features such as age, gender, hypertension status, glucose levels, BMI, and other relevant health indicators.

Our findings indicate that, among the models evaluated, Random Forest achieved the highest accuracy, followed closely by Decision Tree. This suggests that ensemble methods like Random Forest may be particularly effective in handling the complex relationships within the data. On the other hand, K-Nearest Neighbors and Logistic Regression demonstrated lower performance compared to the tree-based models, although their accuracies were still reasonable.

The model performances suggest that incorporating diverse classifiers in a hybrid system could improve the overall prediction accuracy. Additionally, future work may include further model optimization, such as hyperparameter tuning, and exploring advanced models like deep learning-based Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks, which may capture temporal patterns in health data.

The results highlight the potential of machine learning models in the early detection of stroke risk, which can play a crucial role in healthcare systems by enabling proactive and targeted intervention strategies. The success of Random Forest in this task may encourage further use of ensemble models for similar health-risk prediction challenges.

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