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A COMPARATIVE STUDY ON SUSTAINABLE APPROACHES FOR BRAIN STROKE DETECTION

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Abstract: A brain stroke is a medical disorder where the brain is damaged due to a burst in the blood vessels in the brain. These symptoms occur if the supply of blood or any other nutritional resources to the brain are interrupted. The studies indicate that brain stroke is the primary cause of death and disability worldwide. Timely detection of strokes is essential for effective treatment. Current stroke detection techniques include machine learning, but they struggle with complex patterns in medical imaging and need human-designed features. These approaches cause slower diagnosis and erroneous outcomes. To estimate the probability of early-stage brain strokes, the paper experiments using various algorithms, including VGG16, XGBoost, GNN, and EfficientNetB3 architectures. To determine the effectiveness of the algorithms, a reliable dataset for stroke detection was taken from Kaggle website. Several classification models, including XGBoost, VGG-16, EfficientNetB3, and GNN were used. By training the model on a large dataset and classifying using different algorithms the XGBoost has produced the highest accuracy of 97.94% than the GNN, VGG-16, and EffiientNetB3 which produced an accuracy of 73.68%, 87.26%, 75.28% accuracy. This paper showed that XGBoost performed

Index Terms: Extreme Gradient Boosting, Visual Geometric Group-16(VGG-16), EfficientNetB3, Graph Neural Network(GNN), Stroke Detection, XGBoost.

I. INTRODUCTION

Stroke is considered one of the deadliest diseases in the world. In 2016 stroke was ranked 2nd in the disease that causes death under heart disease[1]. Meanwhile, in 2019 there were 12.2 million stroke cases with a worldwide frequency of 101 million, and 6.6 million cases of death were caused due to brain stroke[2] A brain stroke, occurs when the supply of blood is abruptly cut off to certain parts of the brain. This disruption can result from a haemorrhagic stroke, which is the burst of a blood vessel inside the brain, or from an ischemic stroke, which is a blockage in the blood arteries supplying the brain. Five factors cause stroke: high blood pressure, high BMI, high blood glucose levels, high ambient particulate matter pollution, and smoking habits[2]. The urgency in recognizing these symptoms cannot be overstated, a swift medical intervention is crucial for minimizing the long-term impact of a stroke and preventing irreversible damage. Detecting brain strokes involves various approaches, and advancements in medical imaging and machine learning have contributed to more accurate and timely diagnoses. Several physical, neurological examinations and brain imaging are used for diagnosing stroke. Brain imaging consists of a Computed Tomography (CT) scan or Magnetic Resonance Imaging (MRI)[1]. Many other imaging techniques other than CT scans, MRI, and machine learning algorithms, for brain stroke detection are Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT). They provide functional information, supporting in the evaluation of cerebral blood flow and metabolism. These techniques offer valuable insights into the physiological aspects of stroke. But, their disadvantage lies in lower spatial resolution compared to CT and MRI. Each imaging modality plays a vital role in the detailed evaluation of strokes, and the choice depends on the specific clinical scenario and the desired level of details required for accurate diagnosis. Comprehensive pre-processing, addressing accuracy and reliability, becomes essential for data quality improvement. For the analysis and model development of the dataset steps like cleaning, integration, reduction, and transformation are used. [3]The VGG16 algorithm operates on brain stroke detection through a process of deep learning and image classification. Utilizing a convolutional neural network (CNN) architecture, VGG16 extracts complex hierarchical features from brain images, sensitive patterns that distinguish between normal and stroke-affected regions. At the beginning the model is trained on a dataset containing labelled brain images, and the algorithm learns to map the distinctive features associated with brain stroke. The convolutional layers within VGG16 play a crucial role in capturing spatial hierarchies of features, while fully connected layers make the final detection. Once the model is trained it can analyze new, unseen brain images and classify them as either stroke or not. [4] EfficientNetB3 follows a concept called compound scaling, which uniformly scales the network's depth, width, and resolution. The convolutional layers of EfficientNetB3 extract hierarchical features from input images, capturing important patterns and structures indicative of brain abnormalities, including strokes. These features encode both low-level image characteristics (edges and textures) and high-level semantic information relevant to stroke detection. [5]Graph Neural Network (GNN) produces a holistic model for the task of brain haemorrhage segmentation. GNNs work based on the principle of neighbourhood aggregation thus providing a reliable estimate of global structures present in images. It is well-suited for capturing the intricate connectivity patterns of the brain's vascular system, which play a crucial role in stroke detection. By representing CT scan images as graphs, where nodes correspond to brain regions and edges represent vascular connections, GNNs can effectively model the spatial relationships and topology of the brain's vascular network.[6]XGBoost is a good application of the gradient argumentation technique.. it consists of a linear version, and the newborn tree may be a method that makes use of different AI algorithms to check whether a fragile newbie would produce a trustworthy newbie in order to increase the version's accuracy. XGBoost has the ability to handle complex datasets and deliver high-performance detection. Leveraging its strengths, researchers and medical professionals have begun applying XGBoost to analyze CT scan images with the aim of detecting brain strokes swiftly and accurately.

II. Literature Survey

Senjuti Rahman et al. [6] used several classification models, including the extreme Gradient Boosting algorithm (XGBoost), Ada Boost, Light Gradient Boosting Machine, Random Forest, Decision Tree, Logistic Regression, K Neighbours, SVM - Linear Kernel, Naive Bayes, and deep neural networks (3-layer and 4-layer ANN) were successfully used for training in this study for classification tasks. 5110 rows and 12 columns made up this dataset. The output column's stroke has a value of either 1 or 0. A stroke risk was found when the value1 was detected, but a stroke risk was not found when the value 0 was displayed. The ANN algorithm has demonstrated promising results among the different deep learning techniques. The three layer deep neural network has produced a higher accuracy of 92.39.

Viswa Priya et al.[7] combined techniques of Machine Learning (ML) and Deep Learning (DL) techniques play the vital role in Disease Prediction. The proposed model will work on the Hybrid ANNRF (Artificial Neural Network-Random Forest).The most widely used dataset is. Electronic Health Record (EHR). And the other format of data sets are ECG, EEG, EMG Bio signals and MRI/CT scan Images. Various techniques can be used to handle these different datasets. The utilized dataset may contain some unwanted noise and mislaid data. And hence the dataset should be pre-processed, so that noise and missed data has been removed. The pre-processing is test on each input features to eliminate the unrelated data. The Correlation between the attribute can calculated and this leads to high efficiency of predicted output. The accuracy of developed prediction models is calculated using 9 features by hybrid classification algorithm. With this proposed model, it is mainly to explore the difference between training and testing dataset. The hybrid architecture was run for specified times with maximum number of 100 epochs each., 94% classification accuracy can be attained with the suggested approach.. The combined characteristics of ANN and RF lead to the proposed hybrid ANNRF approach.

Aditya Rajbongshi et al.[8]. Using machine learning algorithms to identify risk variables in a promising method. The "brain stroke dataset" was used in the model's construction. Random Forest (RF) is used in the training and testing procedure. Brain strokes can be prevented by early detection, which can reduce the death toll. Classifiers such as Support Vector Machine (SVM) and Decision Tree (DT) are used. Using performance evaluation criteria including accuracy, sensitivity (SEN), error rate, false-positive rate (FPR), false-negative rate (FNR), and root mean square, the performance of each classifier has been estimated. error, and log loss. At last, while utilising the RF classifier, our suggested model yielded the highest accuracy, 95.30%. The model needs to be generalized with different feature selection algorithms and make it robust against datasets with a lot of missing data to improve the accuracy.

K.Sudharani et al, [9] . focused on the development and evaluation of a method for the automated identification and classification of brain stroke images. The main objective of this paper is to access the performance of two classification algorithms namely K-NN and MMD for on of stroke images. It used different distance metrics in classification algorithms, including Euclidean, Sum(Manhattan) and Maximum distances. They tested their proposed algorithms on dataset of MR images. The results indicate that the identification score for K-NN and MMD methods is higher comparatively. The paper contributes to the field of medical image analysis and provides insights into the use of LabVIEW software for Stroke Detection.

Naufal Riz Kifli et al.[10] addressed the problem of predicting the potential for a person to have a stroke based on various risk factors. The authors used CNN to train the dataset. Several Machine Learning and Deep Learning models have been applied to different datasets to predict stroke. Its dataset includes attributes such as gender, age, hypertension, heart disease, marital status, occupation, residence type, glucose level, BMI, smoking status, and target variable. The authors conclude that their research contributes to early stroke prediction and prevention. The CNN architecture developed in this study can be used for wider applications in healthcare.

Srinivas, Joseph Prakash Mosiganti, [11] discusses the critical medical emergency of brain strokes, which occur when blood supply to a part of the brain is stopped, resulting in the death of brain cells. To improve stroke detection, the authors proposed an ensemble machine learning model that combines various classifiers such as Random Forest, Extremely Randomized Trees, and Histogram-Based Gradient Boosting. The study primarily focuses on classifying stroke types, focusing to optimize resource allocation, reduce healthcare costs, and introduces a simple intelligence-based optimization to enhance classification accuracy. The proposed model achieved an amazing accuracy of 96.88% using a stroke prediction dataset from the UCI machine learning repository.

Oznur Ozaltin et al.[12] focused the time-sensitive nature of this medical condition. To address this, the authors proposed the use of artificial intelligence algorithms for the rapid classification of brain stroke CT images. They introduced a new convolutional neural network architecture named OzNet and combined it with various machine learning algorithms for binary classification. Through their approach, they achieved an accuracy of 98.42% and an AUC of 0.99 for detecting strokes from CT images, with a focus on the hybrid algorithm OzNet-mRMR-NB.

Tahia Tazin et al.[13] It employs various machine learning models, including Logistic Regression, Decision Tree Classification, Random Forest Classification, and Voting Classifier, to predict the likelihood of a stroke using physiological parameters. With an accuracy of 96% Random Forest has exhibited the highest accuracy. The study made use of publicly available dataset of Stroke Prediction and achieved significantly improved accuracy compared to previous researches, suggesting increased reliability. Multiple model comparisons validate their robustness.

Dhyey v.Deasai et al.[14] examines eight classifiers Logistic Regression, SVM, Random Forest, Decision Tree, KNN, Naive Bayes, and ensemble models utilizing a dataset from Kaggle. Additionally, Logistic Regression achieved the highest accuracy of 97%, while the SVM and Random Forest at 96%, with the Ensemble model hitting 95%. The study covers pre-processing techniques to refine the dataset, balancing data for accuracy improvement, and attributes crucial for model performance evaluation. Through diverse model evaluations, it seeks to contribute to the development of reliable predictive tools for stroke identification.

Qingyu Zhang [15] The study examines various research papers and their outcomes in employing deep learning models for diagnosis. The important contributions include a modified U-Net model with data augmentation for intracranial haemorrhage detection, showing significant promise, especially for larger haemorrhages. An inception network, known as DL-ICH, demonstrated higher accuracy, in haemorrhage classification. Overall, the model underscores the potential of deep learning to fasten and simplify the accuracy of brain tumour and intracranial haemorrhage diagnosis.

III. PROPOSED METHEDOLOGY

The existing model for brain stroke detection envisions the stroke using machine learning algorithms with numerical datasets. From the performance analysis, it is observed that Naïve Bayes performs better than other models. The above-mentioned machine learning models lack real-time deployment as stroke can be specifically identified using (CT / MRI) scan imaging. To overcome these issues the proposed model with deep learning techniques is introduced. The proposed model for Brain Stroke Detection aims to predict the stroke using the Deep Learning Techniques. The model analyzes brain CT scan images by identifying patterns and features indicative of stroke. Various Deep-Learning architectures VGG-16 (Visual Geometry Group-

16), XGBoost, GNN(Graphical Neural Network), and EfficientNetB3 were trained on the data to accurately predict the risk of stroke allowing for early intervention. The proposed model enhances the accuracy and efficiency of brain stroke detection, contributing to timely medical interventions .

The procedure for detecting stroke is described below :

A diverse dataset of Brain CT scan images is gathered from the Kaggle repository containing normal and stroke-affected images for training the model. Features were identified based on the loss of grey-white differentiation, disruption of left and right-sided symmetry, and "hyperdense" which signifies a blood clot, from the dataset that is likely to be informative for stroke detection. Extracted features are normalized to ensure they have similar ranges, which can improve model performance. Missing data, outliers, and inconsistencies in the dataset are handled. The VGG-16, XGBoost, GNN, and EfficientNetB3 models were constructed to detect the indicative of stroke. Architectural parameters and hyperparameters are subject to experimentation. The dataset is partitioned into training, testing, and validation subsets. The VGG-16, XGBoost, GNN, and EfficientNetB3 models were trained on the training data, with validation data used to mitigate overfitting concerns. The model learns to identify patterns and relationships in the data that are indicative of stroke presence.

3.1 VGG16 (Visual Geometric Group-16)

To boost accuracy and speed up model creation, we adopt the VGG-16 architecture with transfer learning for brain stroke categorization. The model is first loaded to process greyscale images of size 224x224 pixels. The model architecture includes multiple blocks of convolutional layers followed by max-pooling layers. Each block starts with two convolutional layers, applying a Rectified Linear Unit (ReLU) activation function, and is followed by a max-pooling layer. The number of filters in each convolutional layer increases progressively across the blocks, starting with 64 filters and doubling in subsequent blocks (64, 128, 256, 512). A custom model was designed on top of the VGG-16 base, consisting of a flattened layer that transforms the output into one-dimension, and then passed through three fully connected Dense layers, each utilizing a ReLU activation function for the classification task, employing the softmax activation function to produce class probabilities. To train the model, it is compiled using the Adamax optimizer with a learning rate set to 0.001. Categorical cross-entropy loss is employed, which is well-suited for multi-class classification tasks. The model's performance is evaluated using the accuracy metric during training.

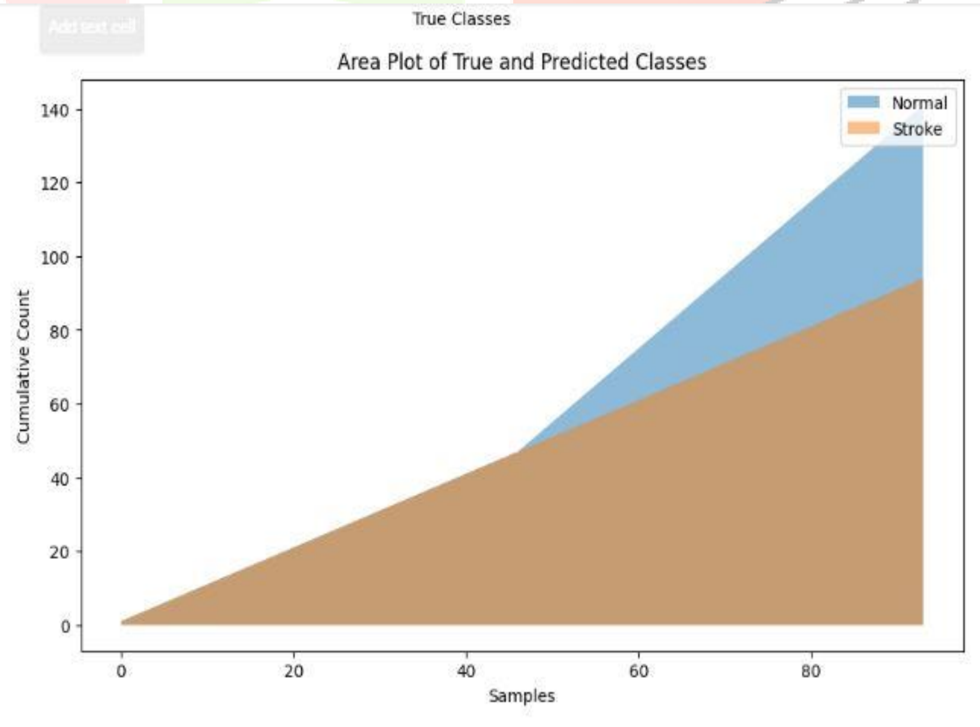

Fig. 1 vgg-16 true classes graph

3.2 EfficientNetB3

EfficientNetB3 is a CNN (convolutional neural network) architecture. The model is loaded by the URL of the pre-trained EfficientNetB3 model and is specified with the input shape as (224, 224, 3) to match the expected input size of the model. A pre-trained EfficientNetB3 model is used as a base architecture. The pre-trained model's weights were fine-tuned on the brain imaging dataset to adapt the model to the specific characteristics of brain images. A sequential model is created with the loaded model as the first layer followed by fine-tuning with a dense layer with a single unit and sigmoid activation function. This configuration is suitable for binary classification tasks. The accuracy metric, binary cross-entropy loss function, and Adam optimizer are used in the compilation of the model. Metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC) can be used to evaluate the model's performance.

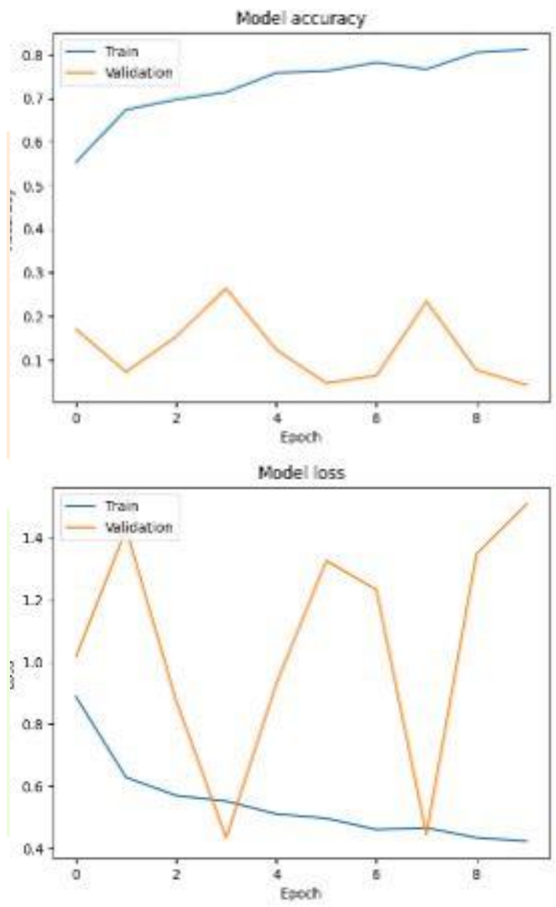

Fig. 2. efficientNetB3 model accuracy and model loss graph

3.3 XGBoost(Extreme Gradient Boosting)

An enhanced distributed gradient boosting library is called Extreme Gradient Boosting. It functions by adding predictors to an ensemble one after the other, each of which minimizes the loss function and corrects the one before it. The XGBoost classifier model is initialized with default hyperparameters. The model performs feature extraction and feature classification. Initially, the feature extractor extracts features from the image data set Then XGBoost trains and classifies the images using extracted features. Because of the decreased model complexity, XGBoost augments the conventional function with regularisation. The training data are provided to the model for learning patterns and relationships between the features (image data) and the target labels (class labels). The trained model's performance is evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score. Techniques for cross-validation may also be used to guarantee the resilience of the model.

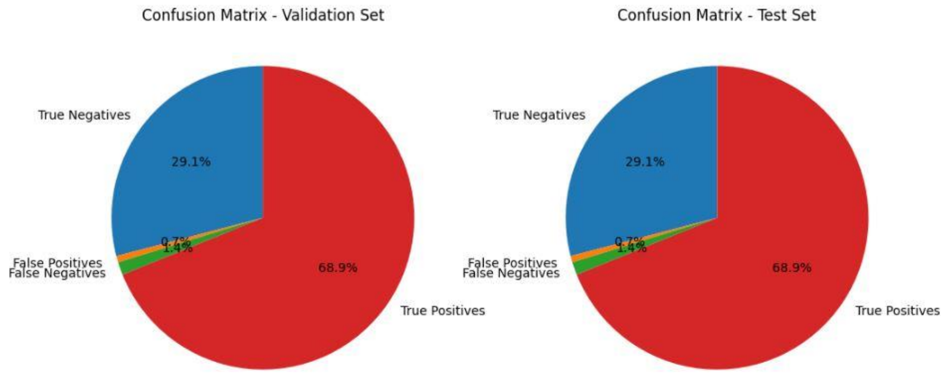

Fig.3. xgboost confusion matrix

3.4 GNN(Gradient Neural Network)

GNN excels at understanding complex connections between different brain areas and synthesizing data from brain CT scan images. It excels at tracking changes over time and across brain regions affected by stroke. It defines the input layer with the same shape as the MobileNetV2 input passes through the base model to extract features then it adds a global average pooling layer to reduce the spatial dimensions. GNN applies dropout regularization to prevent overfitting of the model and adds a dense output layer with a sigmoid activation function for binary classification. It modifies the model architecture by adding additional dense layers and dropout regularizations. Then adjusts the number of units and activation functions in the dense layers. This step allows for flexibility in adapting the model architecture to better suit the dataset and improve performance. GNN helps in fine-tuning (adjusting model parameters) and compiles the model with a lower learning rate. evaluates the fine-tuned model's performance on the validation and test datasets.

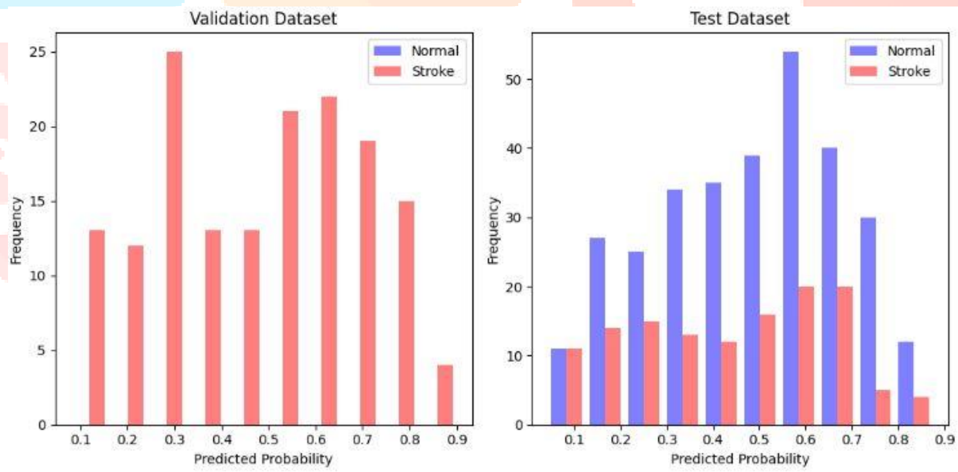

Fig. 4. gnn validation and test dataset graph

IV. RESULTS AND DISCUSSIONS

This paper detects the stroke using various algorithms such as VGG-16, XGBoost, GNN and EfficientNetB3. It demonstrates the following:

4.1Transfer Learning

For particular tasks like stroke diagnosis, pre-trained deep learning models—such as those trained on massive picture datasets like ImageNet—can be improved upon on smaller medical imaging datasets. When there is a shortage of labelled medical imaging data, transfer learning can help accelerate convergence and potentially enhance the performance of the model by utilizing information from one domain to another.

4.2 Hierarchical Representation

Multiple layers of interconnected neurons make up deep learning architectures, which enable them to learn hierarchical representations of data at various levels of abstraction. This hierarchical structure may enhance the discriminatory capacity of the model for stroke detection by capturing both high-level abstract notions and low-level features.

4.3 Automatic Feature Learning

When working with raw data, such as medical pictures (MRI or CT scans), deep learning models can automatically identify pertinent features.

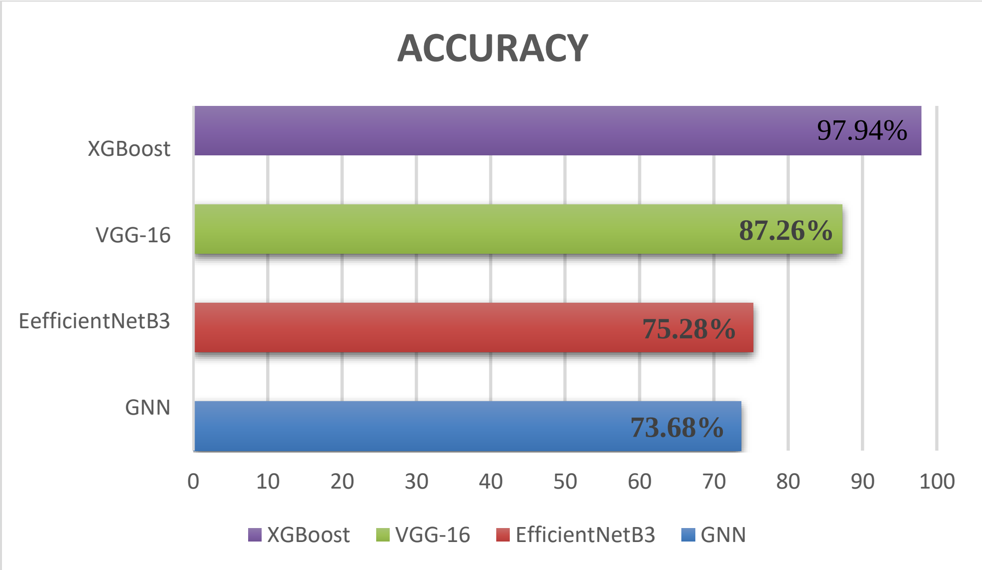

Fig. 5.comparison accuracy among four classifiers

V.CONCLUSION

This paper explores the potential of four different algorithms, including VGG-16, EfficientNetB3, GNN, and XGBoost, in accurately detecting brain strokes. The study uses CT scan datasets to demonstrate the algorithms' potential in identifying stroke-related anomalies, aiding medical professionals in timely diagnosis and intervention. The XGBoost classifier outperforms other classification algorithms with a high-impact, 97.94% accuracy rate, demonstrating the high-impact potential of these algorithms in brain stroke detection. Future work aims to expand datasets, improve model resilience, generalize feature selection strategies, and use image segmentation for stroke area identification, ultimately aiding in early stroke therapy and patient healing.

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