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Deep Learning-Based Multi-Class Stroke Detection Using CNN

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Abstract

Stroke is a critical medical condition caused by an interruption of blood flow to the brain that leads to severe neurological damage or death if not properly diagnosed and treated. Traditional stroke diagnosis employs manual MRI and CT scan examinations, which are subjective, time-consuming, and prone to human error. Previous models were primarily binary classifiers that could only determine the presence or absence of a stroke, which is not adequate for proper treatment[2].To overcome this shortcoming, we developed our own CNN-based model that first detects the presence of a stroke and then classifies it as ischemic stroke, haemorrhagic stroke, or normal cases. This multi-classification is more accurate and provides fine-grained information needed for medical decision-making.Our approach compared to traditional approaches and previous models is more accurate, quicker, and more accurate in stroke classification. With deep learning, our model allows for earlier detection of a stroke, less human error, and better patient outcomes through automatic and accurate diagnosis.

Keywords: Convolutional Neural Network, Brain Stroke, Ischemic Stroke, Hemorrhagic Stroke, Deep Learning

1. Introduction

A cerebrovascular accident, or stroke and brain attack as it is also known, is a condition in which there is a decrease or stoppage of the supply of blood to the brain, thereby removing neuronal cells from the necessary supply of oxygen and nutrients. Due to this deprivation, cell death ensues and is followed by neurological injury. It is one of the leading causes of death worldwide and affects an estimated 15 million people annually with 5.8 million of them dying as a consequence. It is estimated that a stroke will affect one in six people at some time or another during their lifetime.

Cerebral strokes are divided into two major categories:

Ischemic Stroke –

Narrowing or occlusion of the arteries that interrupts blood flow to the cerebral area is the main etiologic factor for this syndrome. This mechanism is responsible for almost 87% of the overall stroke attacks. The blockage can be due to the development of blood clots (thrombosis) or lipid plaque deposition (atherosclerosis). Emergency medical care, like the intravenous administration of thrombolytic drugs (popularly known as clot busters) or mechanical thrombectomy, is necessary to recanalize occluded vessels, restore normal circulation, and avoid permanent damage.

Hemorrhagic Stroke –
Bleeding within the brain due to a ruptured blood vessel, leading to raised intracranial pressure and potential damage to the brain. The causes of a brain stroke are high blood pressure (hypertension), aneurysms, arteriovenous malformations (AVMs), and trauma to the head. Emergency care is needed in an attempt to prevent further bleeding, decrease brain swelling, and prevent further complications.
General Symptoms of Cerebral Stroke
Early identification of stroke symptoms leads to early medical intervention, which prevents complications and improves recovery rates. The most commonly encountered symptoms are:

- Sudden weakness or numbness in the face, arm, or leg, on one side of the body.
- Difficulty in speech or understanding, typically with confusion.
- Distant or absent vision in both or a single eye.
- Sudden headache with no reason, sometimes accompanied by dizziness or nausea.
- Loss of coordination and balance, leading to ambulation problems.
- Dropping of the face, in which half the face seems to be askew or hangs on smiling.

The BEFAST acronym, short for Balance, Vision changes, Drooping face, Weak arm, Slurred speech, and Time to call an ambulance, is commonly employed for rapid recognition of stroke symptoms and early calling of emergency medical staff. Associated Research The diagnosis of cerebrovascular accidents has improved significantly with advancements in deep learning and machine learning algorithms. Gaidhani et al. [2] discussed the use of Convolutional Neural Networks (CNNs) for the detection of stroke, using deep learning algorithms to diagnose medical imaging modalities such as MRI and CT scans. Their research identifies the capability of CNNs to increase diagnostic precision, make automating stroke detection more convenient, and reduce human error in the interpretation of medical images. In contrast, Ravi Kumar et al. [1] discussed machine learning algorithms for stroke detection, using methods such as decision trees, support vector machines (SVM), and neural networks. Their research attempts to investigate structured medical data, such as symptoms of the patient and risk factors, to derive better stroke classification and early diagnosis. AlthoughPrepare both research papers add to the evolution of stroke detection, the former deals with more CNN-based image classification, while the latter uses a wide range of machine learning methods to achieve better predictive outcomes.

1.2 OBJECTIVE

The main goal of the current study is to create a Convolutional Neural Network (CNN) model that is efficient in classifying brain scans into three categories: Ischemic Stroke, Hemorrhagic Stroke, and Normal. In contrast to the majority of the current studies that have maintained binary classification (stroke or non-stroke) as a top priority, the current study introduces a new approach with multi-class classification for the detection of stroke. This approach allows for accurate differentiation between hemorrhagic and ischemic strokes, a consideration that is of immense value in facilitating timely and suitable medical intervention.

By employing deep learning models, our approach improves the diagnostic process by minimizing the need for human interpretation, which is time-consuming and error-prone. The high accuracy of our model allows clinicians to obtain accurate insights that facilitate the achievement of optimal patient outcomes. In addition,

By utilizing deep learning methods, our model improves the diagnosis process by lessening the dependence on human interpretation, which usually takes tremendous amounts of time and is prone to errors. The high classification accuracy makes it possible for medical personnel to make valid conclusions, ultimately resulting in enhanced patient outcomes. Furthermore, our study provides a foundation for future development in computerized stroke diagnosis, whereby real-time detection may be utilized in clinical practice.

Here's an analysis of global brain stroke cases from 2019

Global Brain Stroke Case s (2019-2023) – Insights

- The bar graph represents the global brain stroke cases over the last five years
- The number of new stroke cases worldwide remains
- consistently high, ranging in tens of millions annually.
- There is a gradual increase in global stroke cases from 2019 to 2023, indicating a rising trend in stroke prevalence.

The scale suggests that over 14 million new cases occur globally each year.

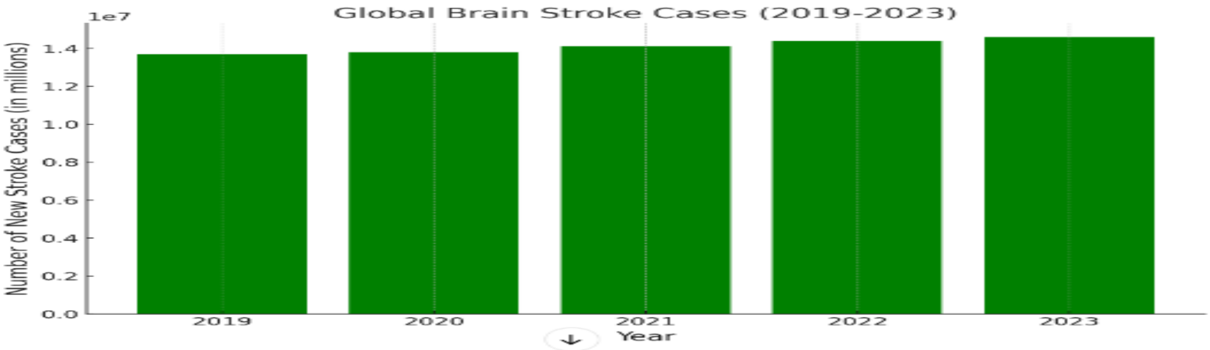

Fig. 1 Bar Graph of brain Stroke Worldwide

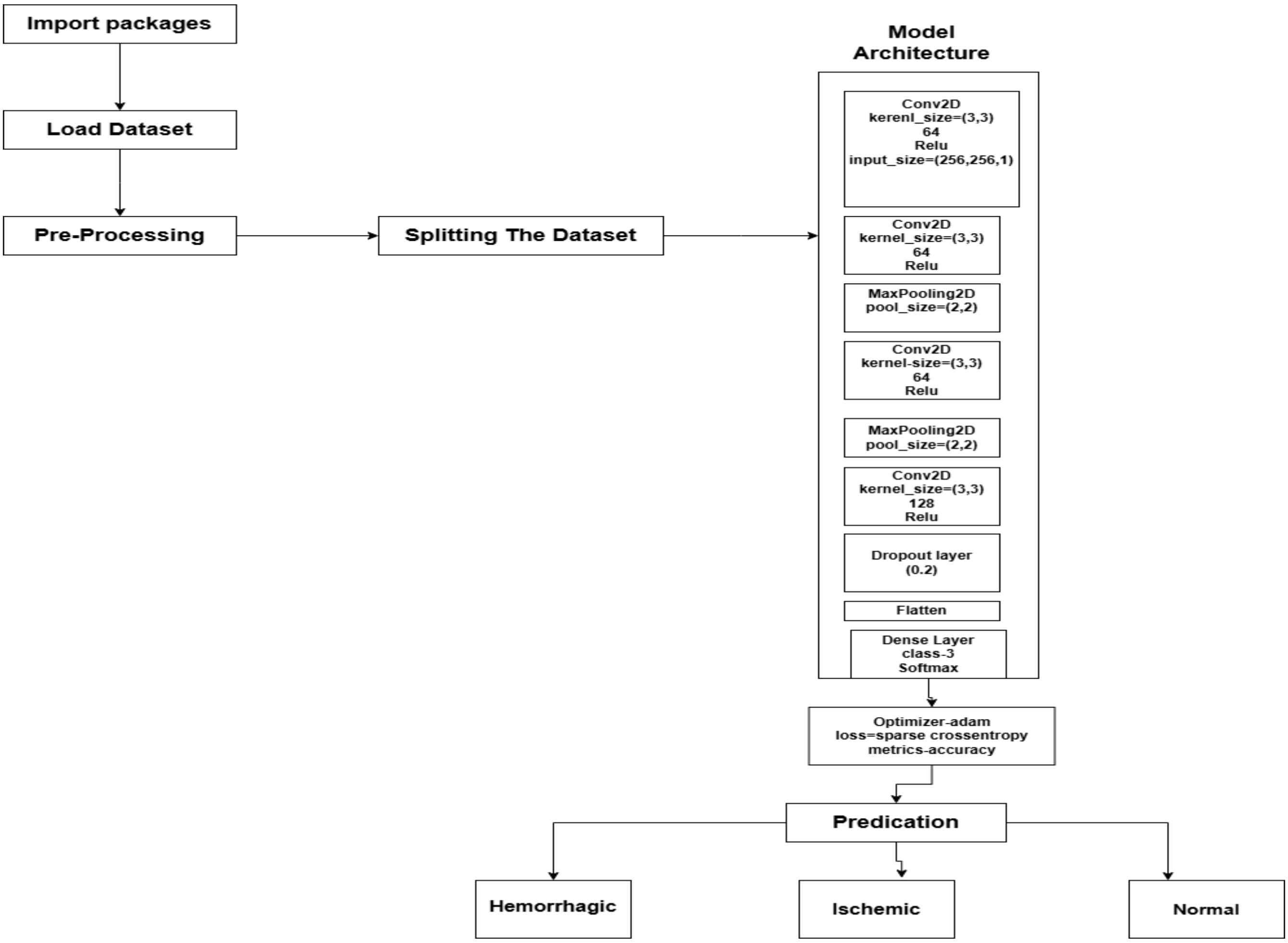

Fig .2 Model Architecture

2. Proposed Methodology

We are utilizing a proprietary Convolutional Neural Network (CNN) architecture to perform multi- class stroke classification. Unlike standard binary stroke classification algorithms, which provide only a prediction of whether a stroke exists or not, our algorithm initially recognizes the absence or presence of a stroke and goes on to classify the stroke into ischemic, hemorrhagic, or normal classes. This multi-class classification contributes to more precise diagnosis accuracy and results in improved medical decision-making and earlier interventions

.2.1 Data Collection

We received a dataset for this study from Kaggle, which consists of approximately 7,500 MRI and CT brain scan images labeled into three classes: Ischemic Stroke, Hemorrhagic Stroke, and Normal. The dataset was organized into three separate folders, each containing images belonging to its own class. This diverse dataset allows the model to learn robust and generalizable features between different stroke types.

```
/dataset
    /train
        /hemorrhagic
        /ischemic
        /normal
    /test
        /hemorrhagic
        /ischemic
        /normal
    /validation
        /hemorrhagic
        /ischemic
        /normal
```

Fig.3 Dataset Directory Representation

2.2 Preprocessing

1. Resizing

   All the images were resized to 256×256 pixels for a uniform input size. MRI scans are available in various resolutions, and these can cause inconsistencies while training the model. Resizing ensures the models are all equal in size, and this is what optimizes the computational efficiency and allows the CNN model to learn at its optimal capacity

2. Grayscale

   Since MRI scans predominantly contain structural information rather than color information, we have all the images converted to grayscale. Color channels reduces computational complexity without impacting crucial features required for stroke classification. This will help ensure that the model highlights the basic differences in intensity, which play a critical role in identifying ischemic and hemorrhagic strokes.

3. Normalization

   We normalized by rescaling pixel values to the range [0,1] by dividing them by 255. Normalization makes the training process stable, prevents large weight updates, and keeps pixel values in a standard range. Normalization speeds up convergence and helps the model generalize more to unknown MRI scans

4. Scaling(Optional)

   Scaling techniques are employed to modulate intensity variations in MRI images to further support feature extraction. This step is not mandatory but enhances the contrast, with stroke-damaged areas being more prominent than normal brain

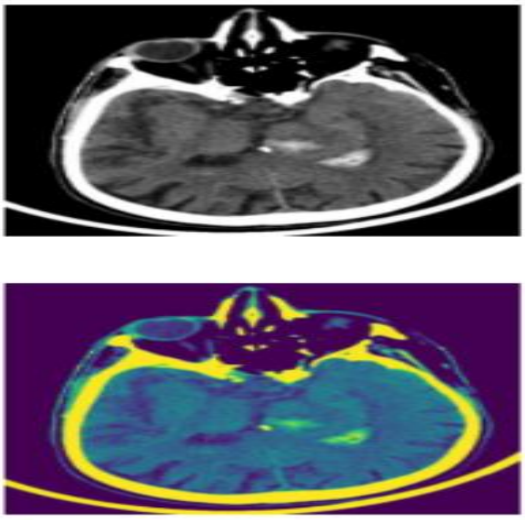

Fig.4 Preprocessed image

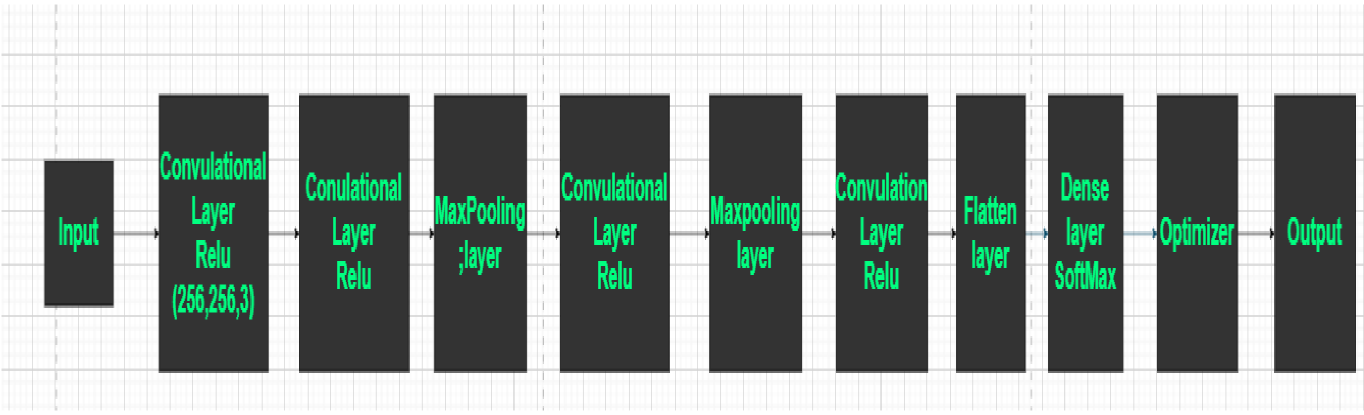

Fig .5 Architecture of Proposed Model

3. CNN Architecture

The suggested Convolutional Neural Network (CNN) model is intended for brain stroke classification automatically, separating Ischemic, Hemorrhagic, and
Normal brain scans. The structure includes several convolutional layers for feature extraction, pooling layers for reducing dimensions, and fully connected layers for classification

3.1 Input layer
The model begins with an input layer that takes images of brain scans with the size 256×256×3. The three channels are
for RGB color space, which is preserved in order to maintain fine texture details in medical scans. Pixel values are
normalized to 0 to 1 so that the training is stable and there are no problems associated with different scales of intensity.

3.2 Convulation Layer

The Convolutional Layer is the fundamental block of the CNN model, tasked with learning spatial hierarchies and patterns automatically from brain stroke images. In our architecture, the initial convolutional layer receives an input image of 256×256×3 size, where 3 indicates the RGB channels. The layer convolves 8 learnable filters (kernels) of 3×3 size over the image to capture local patterns like edges, textures, and intensity variations in the brain scan.

Each filter traverses the input image, carrying out an element-wise multiplication and then summation to produce a feature map. This process captures essential features like stroke-affected areas and structural problems in the brain.

3.2.1)Activation Function: ReLU

Following convolution, a Rectified Linear Unit (ReLU) activation is used to bring in non-linearity and allow effective gradient propagation. The ReLU function is given by:

$F(x)=\max(0,x)$

The activation enables the model to learn sophisticated patterns by removing negative values and only letting important positive activations pass through, enhancing convergence speed and avoiding the vanishing gradient issue.

3.3 Pooling layer

The Pooling Layer is a pivotal component of the suggested CNN model in that it decreases the spatial size of feature maps without sacrificing the most crucial information. For this model, a MaxPooling layer with the pool size (2×2) is utilized after every convolutional layer. This process decreases computational complexity without losing vital stroke-related features, thus making the model more efficient. The main purpose of the pooling layer is to obtain dimensionality reduction, feature invariance, andoverfitting suppression. Through taking the maximum value of every 2×2 region, MaxPooling guarantees that the most important activations are preserved so that the model can concentrate on important stroke-related patterns while not caring about any worthless details or noise. Here, the input feature map size of 256×256 goes through MaxPooling and is then shrunk to 128×128, then by additional pooling it is brought down to 64×64. This progressive downsampling refines the feature extractions before it is passed through the fully connected layers. MaxPooling over AveragePooling has been used as the former captures the high-intensity features in a better manner, which plays an important role in medical images in identifying regions of stroke attack. By removing redundant features, pooling layers contribute to the development of a more effective and robust stroke classification model, allowing it to differentiate between ischemic stroke, hemorrhagic stroke, and normal brain scans with higher precision.

3.4 Flatten layer

The Flatten Layer acts as a transition layer between the convolutional and fully connected layers of the suggested CNN model. Following feature extraction by the convolutional and pooling layers, the output feature maps remain in a multi-dimensional spatial form. In order for these features to be processed by the Dense (fully connected) layers, the Flatten layer flattens the multi-dimensional feature maps into a one-dimensional vector. This process guarantees that each feature that was extracted has its contribution in the final classification procedure. Since the final pooling layer gives out a smaller feature map, the Flatten layer reshapes these values in one long vector that can actually be efficiently handled by the fully connected layers in order to carry out the classification. This is an important step as it readies the data for learning sophisticated relationships between features and the resultant stroke types—ischemic, hemorrhagic, or normal.

3.5 Dense Layer

The Dense Layer, or fully connected layer, is employed for final classification. Here, Softmax activation function on the output layer is applied for multi-class classification to provide probability scores of all the classes (ischemic stroke, hemorrhagic stroke, and normal). The fully connected layers allow the model to represent complex, high-level information by combining extracted features in previous layers. The Dense layer neurons are given inputs from all the neurons of the Flatten layer above them, enabling end-to-end feature learning. Softmax function is also helpful in normalizing the output into a probability distribution such that the model is able to output the most probable class label of the input brain scan. The Dropout methods can also be applied to prevent overfitting and enhance the model's generalization. This design enables the CNN to identify stroke types precisely, enhancing diagnostic accuracy compared to traditional binary classification techniques.

3.5.1 SoftMax Function:

The Softmax activation function is used in the final Dense layer to handle multi-class classification, ensuring that the CNN model predicts one of the three categories—ischemic stroke, hemorrhagic stroke, or normal. The Softmax function transforms the raw output values (logits) from the Dense layer into probabilities, making them sum up to 1.

3.6 Output layer

The Output Layer is the last step of the CNN model, which is used to generate the results of classification of brain stroke. It contains three neurons, each of which is related to one of the categories of stroke:

- Ischemic Stroke
- Hemorrhagic Stroke
- Normal (No Stroke)

For ensuring the model yields useful predictions, the Softmax activation function is used here. This takes the raw scores (logits) produced by the preceding Dense layer and scales them into a probability distribution in which the sum of all the output values is 1. The class with the highest probability value is picked as the prediction.

3.7 Model Compilation And Optimzation

Once the model's CNN architecture has been defined, the model is compiled to get it ready to learn. Compilation includes choosing an optimizer, loss function, and measuring metric in order to learn efficiently and classify properly.

•Optimizer – Adam (Adaptive Moment Estimation): Adam is a sophisticated optimization algorithm that leverages the advantages of Momentum and RMSprop, dynamically adjusting learning rates for each parameter. It facilitates faster convergence and prevents getting trapped in local minima, making it highly suitable for deep learning applications such as stroke classification.

•Loss Function – Sparse Categorical Cross-Entropy: As the task of classification contains three unique classes (Ischemic, Hemorrhagic, and Normal), Sparse Categorical Cross-Entropy is employed for calculating the discrepancy between predicted and true labels. Unlike standard categorical cross-entropy, it is effective for integer-labeled classes and enhances the performance of the model.

•Evaluation Criterion – Accuracy: Accuracy is used as the primary criterion to measure the performance of the model in identifying stroke types correctly. It measures the ratio of correctly predicted instances to the total predictions, giving a clear idea of the effectiveness of the model.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 64)	640
conv2d_1 (Conv2D)	(None, 252, 252, 64)	36,928
max_pooling2d (MaxPooling2D)	(None, 126, 126, 64)	0
conv2d_2 (Conv2D)	(None, 124, 124, 64)	36,928
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_3 (Conv2D)	(None, 60, 60, 128)	73,856
dropout (Dropout)	(None, 60, 60, 128)	0
flatten (Flatten)	(None, 460800)	0
dense (Dense)	(None, 3)	1,382,403

Total params: 1,530,755 (5.84 MB)
Trainable params: 1,530,755 (5.84 MB)
Non-trainable params: 0 (0.00 B)

Fig.6 Feature Extraction Summary

4. MODEL TRAINING AND EVALUATION

In order to train the Convolutional Neural Network (CNN) efficiently, the dataset was split into three sets:

70% for training – For learning image patterns.
15% for validation – For hyperparameter adjustment and avoiding overfitting.
15% for testing – For testing the performance of the final model on new data

The CNN model was trained with the following hyperparameters:

- Batch Size: 32
- Number of Epochs: 40
- Optimizer: Adam (Adaptive Moment Estimation)
- Loss Function: Sparse Categorical Cross-Entropy

4.1 Evaluation Metrics

The model was tested with four major metrics: accuracy, precision, recall, and F1-score.

4.2. Mathematical Formulation

Precision

is the ratio of correctly predicted stroke types to all predicted cases for that category:

$$\text{Precision}=\frac{TP}{TP+FP} \qquad (1)$$

Recall

counts how many true stroke cases were correctly classified:

$$\text{Recall}=\frac{TP}{TP+FN} \qquad (2)$$

F1-Score

provides a balanced measure of precision and recall:

$$\text{F1−Score}=\frac{2*\ \text{Precision*recall}}{\text{Precsion+recall}} \qquad (3)$$

Accuracy

represents the proportion of correctly classified images out of the total number of images

$$\frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

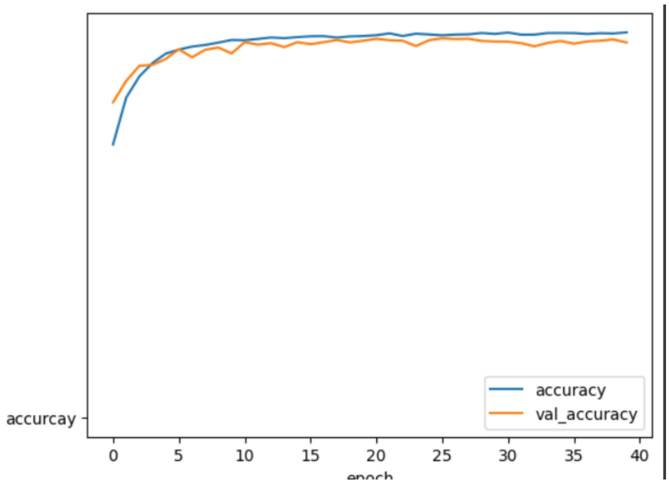

Fig .7 Accuracy vs Validation_accuracy

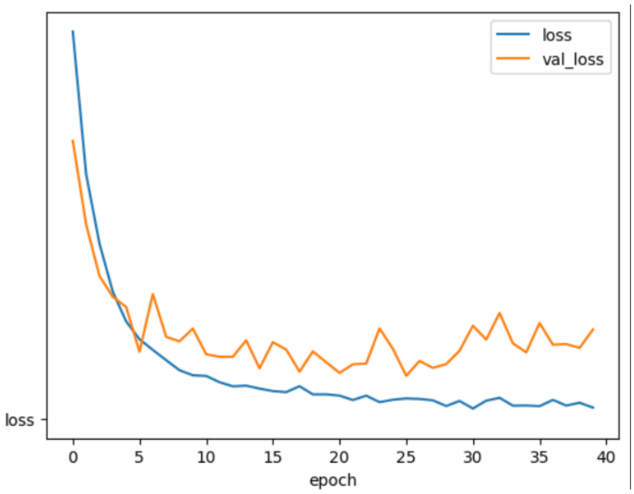

Fig.8 Loss vs Validation_loss

5.Result

The trained CNN model achieved 97% accuracy in the test dataset, demonstrating its ability to distinguish brain stroke images into ischemic, hemorrhagic, and normal classes.

To further examine performance, a classification report was produced, showing precision, recall, and F1-score by class. The results confirm that the model is well performing for every category, with minimal misclassification per class. The results are consistent with the model performing well in all categories, with little misclassification.

Table.1 Pretrained Model Accuracy

Data-set	Prediction type	Proposed model	Accuracy
Brain CT image	Brain stroke	CNN	79%
Brain MRI	Brain stroke	AlexNet+SVM	99.9%
Structured data	Brain stroke	Stacking classifier	98%
Electroencephalogram	Brain stroke	ResNet-50	90%
Brain MRI	Ischemic stroke	CNN-Bidirectional LSTM	94.2%
Brain CT image	Early acute stroke	Advanced XGBoost	97%
Brain CT image	Early brain stroke	GA_BiLSTM	96.45%
Brain CT image	Brain stroke	VGG-19	97.06%

Table.2 Comparisons of Model

Classification Algorithm	Accuracy	Precision	Recall	F1-measure
KNN	95.41%	94.88%	94.61%	94.61%
Naïve Bayes	71.28%	70.91%	74.46%	72.64%
Logistic Regression	83.00%	81.27%	77.46%	79.32%
Decision Tree	93.32%	92.32%	92.34%	92.22%
Random Forest	95.67%	95.69%	94.10%	94.88%
NN-MLP	88.43%	87.48%	84.86%	86.15%
Deep Learning	86.46%	84.72%	83.04%	83.86%
SVM	85.67%	85.03%	80.39%	82.64%
Proposed Model	**97.00%**	**97.00%**	**97.00%**	**97.00%**

Table.3 Classification Report

Class	Precision	Recall	F1-Score	Support
Hemorrhagic	0.97	0.96	0.97	536
Ischemic	0.97	0.97	0.97	531
Normal	0.99	1.00	1.00	530
Accuracy	-	-	**0.98**	1597
Macro Avg	0.98	0.98	0.98	1597
Weighted Avg	0.98	0.98	0.98	1597

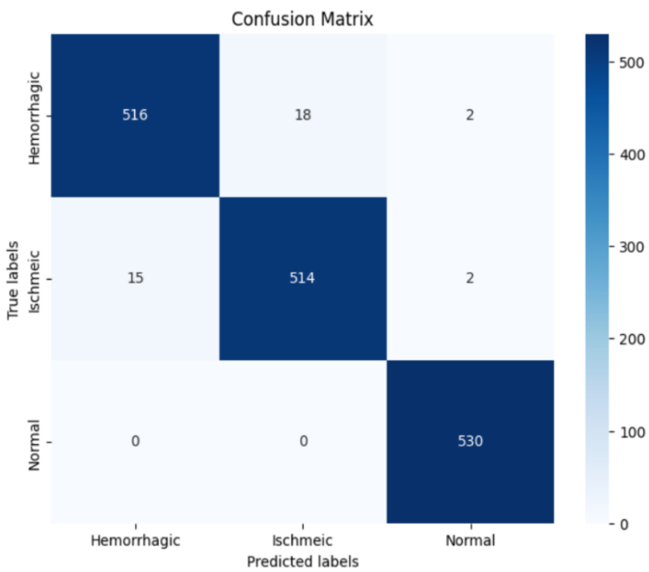

Fig.9 Confusion Matrix

6.Conclusion

This study developed a CNN-based system for multi-class stroke classification with 97% accuracy on the test set. Unlike other binary classification techniques, our system discriminates efficiently between ischemic, hemorrhagic, and normal brain scans. Architectural optimization through ReLU, Softmax, Adam, and Sparse Categorical Cross-Entropy ensured effective feature extraction and classification. Though promising, further improvement through hyperparameter tuning and data augmentation can possibly optimize performance. This research highlights the abilities of CNNs to automate the diagnosis of stroke for faster and more accurate medical decisions.

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