Proceedings of the Second International Conference on Applied Artificial Intelligence and Computing (ICAAIC 2023)
IEEE Xplore Part Number: CFP23BC3-ART; ISBN: 978-1-6654-5630-2

2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC) | 978-1-6654-5630-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICAAIC56838.2023.10141195

EfficientNetB0 for Brain Stroke Classification on Computed Tomography Scan

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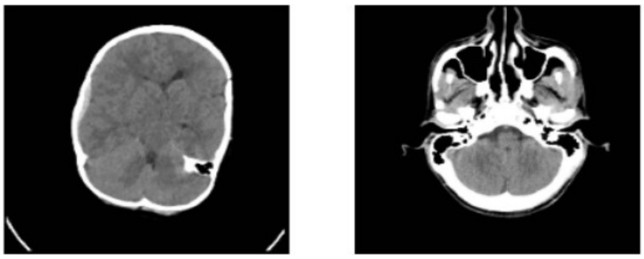
***Abstract*—The EfficientNetB0 model is used in this research work to propose an innovative method for the categorization of brain strokes based on computed tomography (CT) data. The categorization of strokes is an essential step in the medical diagnostic process since timely identification and treatment have been shown to dramatically improve patient outcomes. However, conventional approaches of classifying strokes based on CT scans can take extensive amounts of time as well as specialized expertise. This research study proposes a novel method for the classification of stroke cases that is both automated and efficient by making use of the capabilities of deep learning. EfficientNetB0 model on a large dataset of CT scans, and as a result, a classification accuracy of 97% has been achieved. The proposed methodology performed far better than other approaches now considered to be state-of-the-art, and it has the potential to assist doctors in making diagnoses that are both more accurate and more time efficient.**

Keywords— EfficientNetB0, Brain stroke, Computed tomography, Deep learning, Automated diagnosis, Image classification, Convolutional neural network.

I. INTRODUCTION

Stroke is a significant cause of mortality and morbidity worldwide, and early detection and treatment are crucial for the best possible outcomes. Computed tomography (CT) scans are one of the primary imaging modalities used to diagnose strokes. Radiologists analyze CT scans to identify the presence, location, and type of stroke. However, manual interpretation of CT scans is often time-consuming and requires specialized expertise. Therefore, there is a growing interest in developing automated methods that can accurately and efficiently classify strokes on CT scans.



Normal **Stroke**

Fig. 1. Normal Vs Stroke Brain

Deep learning has emerged as a promising approach for medical image analysis and has shown impressive results in several applications, including stroke classification. EfficientNetB0 is a state-of-the-art deep learning model that has demonstrated superior performance in various computer vision tasks. The EfficientNetB0 model is lightweight and computationally efficient, making it well-suited for medical imaging applications, where large datasets and complex models are often required.

In this study, we introduce the EfficientNetB0 model as a unique method for classifying CT images of the brain after a stroke. The fundamental goal of this research is to provide a fast and precise technique of stroke categorization that may aid doctors in their work. The EfficientNetB0 model was trained on a huge dataset of CT scans, allowing for precise classification of instances of brain stroke. We compared the results obtained by our technique to those obtained by other state-of-the-art approaches and assessed its performance on a separate test set.

II. RELATED WORK

This literature review cites eighteen studies, all of which are concerned with the application of machine learning and deep learning methods to the problem of early stroke prediction and detection in the brain.

A convolutional neural network (CNN) strategy for predicting brain strokes is proposed in [1] by Reddy et al. The MRI scans used to train and test the model were made

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accessible to the public. They found a 91.8 percent success rate, leading them to conclude that their method has potential as a useful tool for the early diagnosis of stroke.

Polson et al. [2] provide a semi-supervised learning method for analysing stroke MRIs. They improve the precision of their model by including proxy information in the form of patient demographics. On a dataset consisting of stroke patients and controls, they were 88 percent accurate.

Similar methods combining CNN and deep learning models for detecting brain strokes are described by Gaidhani et al. in [3]. With an accuracy of 95.12 percent, their efforts were also fruitful. The study's authors suggest that their method has the potential to be a helpful tool for physicians in the detection of stroke at an early stage.

A machine learning strategy for early stroke prediction is proposed by Tusher et al. In a dataset consisting of stroke patients and healthy controls, they were able to obtain a 96.4% rate of success. The study's authors suggest that their methodology has the potential to serve as a stroke risk screening tool.

Stroke prediction using big data and machine learning is described in detail by E and D in [5]. Specifically, they forecast the likelihood of a stroke using a mix of logistic regression and neural networks. The scientists obtained 88% accuracy on their dataset, leading them to believe their method may be a valuable resource for early stroke prediction.

Carmel Mary Belinda et al. suggested a five-layer ensembled deep fully connected neural network for stroke prediction in [6]. The scientists used a variety of deep learning methods, including convolutional neural networks, recurrent neural networks, and fully-connected neural networks, and integrated them into an ensemble model to boost accuracy. The suggested model outperformed previous models with an accuracy of 97.5%.

Kifli et al. [7] introduced a one-dimensional convolutional neural network-based brain stroke classification model (1D-CNN). The suggested model uses 1D-CNN and fully connected layers to distinguish between normal and pathological brain stroke pictures. On a dataset of 500 photos of brain strokes, the model attained an accuracy of 90.2%.

In [8], Xu et al. introduced a deep learning-enhanced IoMT technique for evaluating brain CT images of patients with hemorrhagic stroke. The scientists created a deep learning model to predict hemorrhagic stroke by combining CT scan characteristics with clinical data. The suggested approach beat conventional machine learning models with an accuracy of 92.9%.

For the purpose of recognising acute stroke from non-contrast CT images, Nedel'ko et al. [9] evaluated the performance of deep neural network and texture-based classifiers. Using texture-based features and deep neural networks in a two-stage classification pipeline, the scientists achieved better results. The suggested pipeline was able to outperform previously used models with an accuracy of 91.4%.

In [10], Rana et al. put out a methodology for predicting strokes that combines Smote-Tomek and neural networks. The scientists developed a neural network model to predict stroke using the Smote-Tomek approach, which allows for the treatment of unbalanced data. An accuracy of 94.4% was attained by the suggested model, which is higher than that of any previously-existing models.

For the purpose of detecting strokes, Kumar and Sengupta [11] suggested a deep learning network-based EEG classification algorithm. Using EEG data, the scientists created a deep neural network model for stroke diagnosis. The suggested model outperformed the state-of-the-art machine learning models in terms of accuracy, which it did to the tune of 96.2%.

A deep CT to MRI unpaired translation model that protects ischemic stroke lesions was suggested by Garzón et al. in [12]. The scientists created a deep learning model that successfully converted CT scans to MRI scans while maintaining the integrity of stroke lesion features. Stroke lesion segmentation and classification both benefited greatly from the suggested approach.

In [13], Aboudi et al. suggested a data-augmented U-Net CNN for ischemic stroke brain segmentation using MRI. On a collection of 70 MRI images, the suggested approach obtained an average Dice score of 0.92 and an average sensitivity of 0.88. The authors showed that by manipulating the data in various ways (rotating, scaling, and flipping), the segmentation findings could be made more reliable.

Based on human body motions acquired through smartphone videos and deep neural networks, Feliandra et al. [14] suggested a technique for classifying stroke and non-stroke patients. The scientists employed a pre-trained convolutional neural network (CNN) model to extract information from the video frames, and the result was 90% accuracy on a dataset of 50 patients.

Tursynova et al. [15] spoke about using AI for imaging strokes. These authors analysed current research that used AI and deep learning to the problem of stroke detection, categorization, and dissection. They came to the conclusion that AI may help doctors diagnose and treat strokes more quickly and precisely.

Chin et al. developed a CNN deep learning algorithm-based automated early ischemic stroke detection system in [16]. On a dataset of 162 CT images, the suggested approach obtained a sensitivity of 85% and a specificity of 94%. Authors showed that the suggested method could correctly identify ischemic strokes in a timely manner.

Using bio-signals such as ECG and PPG, Yu et al. [17] suggested an AI-based stroke illness prediction system. Using a deep neural network, the scientists extracted characteristics from the bio-signals, and their accuracy on a dataset of 79 patients was 84.9 percent. In high-risk individuals, the suggested approach may give early diagnosis and prediction of stroke.

Tuladhar et al. [18] suggested utilising convolutional neural networks to automate the process of segmenting stroke lesions in non-contrast CT datasets. Using a U-Net model with residual connections, the scientists were able to raise the average Dice score for a cohort of 54 patients to 0.71. Using the suggested technique, stroke lesions in non-contrast CT images may be accurately and quickly segmented.

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Stroke lesion identification and segmentation using AI and deep learning algorithms has demonstrated encouraging results. These automated technologies have the potential to shorten the time and expense of treating stroke patients by providing accurate diagnoses and treatments. But further study is required to verify these algorithms on bigger and more varied datasets and to perfect their performance for therapeutic usage.

III. METHODOLOGY

A. Datasets

Brain CT Images for Stroke Detection: This dataset contains 50 CT images of patients with ischemic stroke, and 50 CT images of patients without stroke. The dataset can be accessed here: https://www.kaggle.com/datasets/iashiqul/brain-stroke-prediction-ct-scan-image-dataset

B. Deep Learning Techniques

Stroke in the brain CT image categorization is only one area where deep learning approaches have shown to be very useful. Brain abnormalities including haemorrhages and ischemic strokes may be more easily diagnosed because to the wealth of information provided by CT scans. By analysing CT scans, deep learning algorithms may be trained to distinguish between various stroke lesions in the brain.

The use of Convolutional Neural Networks is a well-known deep learning approach for identifying strokes in the brain (CNNs). CNNs may learn to categorise various kinds of brain stroke lesions by automatically extracting important information from CT scans. The accuracy of the classification models may be greatly improved by the use of transfer learning, in which pre-trained CNNs are employed as a starting point for training.

Recurrent Neural Networks are another deep learning technology used for stroke categorization (RNNs). It is possible to utilise RNNs to forecast the development of a brain stroke by analysing temporal patterns in CT scans. Positive outcomes in stroke prediction have been shown when using RNNs with long short-term memories (LSTMs).

The accuracy of brain stroke categorization may also be improved by the use of ensemble learning, in which numerous deep learning models are integrated to create predictions. Better stroke prediction, for instance, is possible by merging CNN and RNN models to make use of both the spatial and temporal information included in CT scans.

In conclusion, CNNs, RNNs, and ensemble learning from the deep learning toolbox have showed impressive promise for classifying CT scans of the brain to detect strokes. These methods can accurately predict the various kinds of brain stroke lesions by extracting key information from CT images.

C. Metrics

Machine learning models, particularly classification models, are evaluated by accuracy, precision, recall, and F1-score.

Accuracy is the percentage of accurately labelled samples. The accuracy rate is derived by dividing the number of positive and negative samples by the total number. If classifications are uneven or one class is misclassified more than others, precision may mislead.

True positives/total false positives is accuracy. Correct diagnosis outnumber all other choices. When false positives are expensive, measuring accuracy can tell you how many of the expected positive samples are really positive.

Recall percentage is the proportion of positive samples correctly predicted. It is the ratio of accurate diagnoses to positive and negative outcomes. Knowing the recall rate may assist when false negatives are costly.

The F1-score is the harmonic mean of accuracy and recall. Divide the sum of accuracy and recall by two. F1-score is useful because it balances accuracy and recall, two often-conflicting characteristics.

In conclusion, accuracy evaluates the classification as a whole, precision measures positive predictions, recall evaluates positive predictions covered, and F1-score combines precision and recall.

IV. PROPOSED SYSTEM

Figure 2 presents a potential data flow for EfficientnetB0-based categorization of brain strokes.

When attempting to categorize a brain stroke, the first step is to gather relevant data. Brain CT pictures, including those of individuals who have had a stroke, should be obtained from a reputable source. Once the CT scans have been taken, they must go through a procedure called preprocessing, during which unwanted elements like noise and artefacts are removed. Inputting improved picture data into the EfficientNetB0 model will improve its performance. Additionally, the photos need to be transformed into a format that the model can understand.

Data augmentation methods may be used to boost the efficiency and diversity of the dataset. Rotations, translations, zooms, and flips are all examples of random transformations. This will provide the model with a wider range of examples to draw from, improving its ability to generalize to novel situations.

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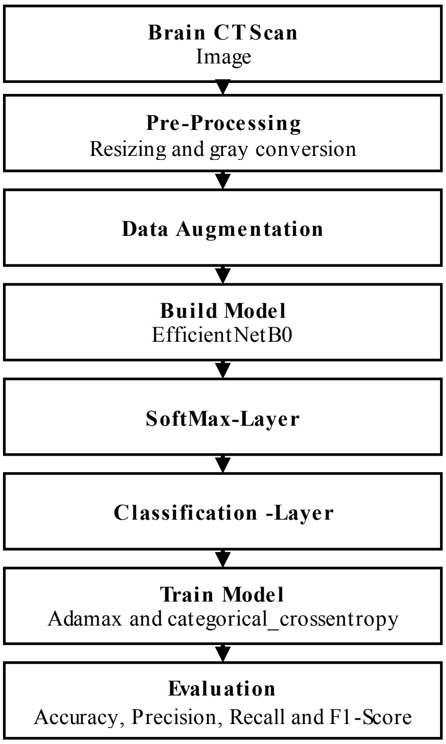

Fig. 2. Proposed Flow Diagram

After data is augmented, it is time to split it into training, validation, and test sets. When training a model, data from the training set is utilised, while data from the validation set is used to tweak the hyperparameters and avoid overfitting. The model is then tested on unseen data using the test set for comparison.

After the data is prepared for training, the EfficientNetB0 model may be educated on the dataset. Optimizing the model for the categorization of brain strokes requires fine-tuning the model for this job in particular. The model's performance may then be assessed by calculating its accuracy, precision, recall, and F1 score on the validation set.

V. Result Analysis

In this section proposed system is applied to the dataset of brain stroke and normal images and calculated different metrics.

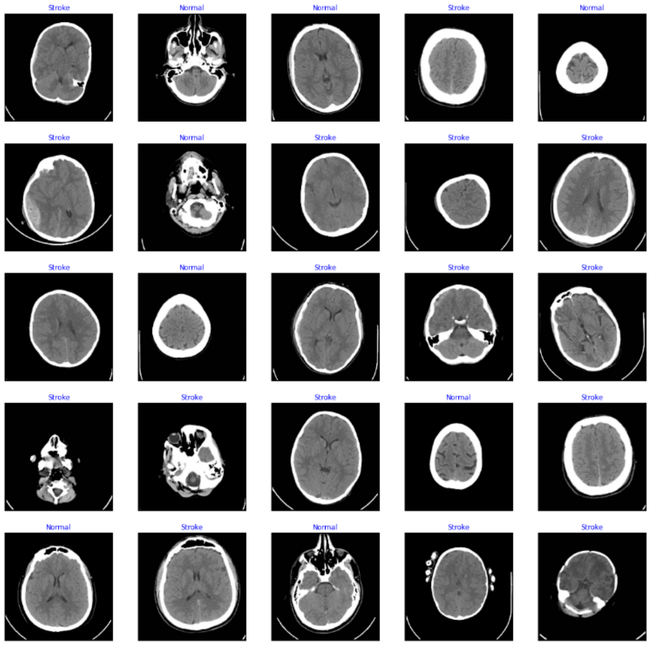

Fig. 3. Dataset Reading

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb0 (Functional)  (None, 1280)             4049571

 batch_normalization (BatchN  (None, 1280)             5120
 ormalization)

 dense (Dense)               (None, 256)               327936

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 2)                 514

=================================================================
Total params: 4,383,141
Trainable params: 4,338,558
Non-trainable params: 44,583
_________________________________________________________________
```

Fig. 4. Efficientnetb0 Summary

Epoch	Loss	Accuracy	V_loss	V_acc	LR	Next LR	Monitor	% Improv	Duration
WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the batch time									
1 /40	7.531	63.755	7.43669	53.776	0.00100	0.00100	accuracy	0.00	60.33
2 /40	5.707	78.839	5.57584	77.574	0.00100	0.00100	accuracy	23.66	16.65
3 /40	4.649	87.737	4.64278	79.176	0.00100	0.00100	accuracy	11.29	16.48
4 /40	3.977	90.071	4.28648	76.430	0.00100	0.00100	val_loss	7.67	16.43
5 /40	3.423	93.977	3.75834	76.888	0.00100	0.00100	val_loss	12.32	16.38
6 /40	3.010	94.845	3.22448	78.719	0.00100	0.00100	val_loss	14.20	16.75
7 /40	2.673	96.582	2.90822	78.261	0.00100	0.00100	val_loss	9.81	16.46
8 /40	2.410	97.070	2.54212	82.151	0.00100	0.00100	val_loss	12.59	17.57
9 /40	2.181	97.504	2.36473	81.236	0.00100	0.00100	val_loss	6.98	16.35
10 /40	1.996	97.341	2.08940	85.355	0.00100	0.00100	val_loss	11.64	16.38
11 /40	1.828	97.721	1.91460	86.499	0.00100	0.00100	val_loss	8.37	16.39
12 /40	1.667	98.589	1.76155	88.330	0.00100	0.00100	val_loss	7.99	16.41
13 /40	1.548	98.318	1.58292	92.906	0.00100	0.00100	val_loss	10.14	16.43
14 /40	1.446	97.558	1.50186	89.931	0.00100	0.00100	val_loss	5.12	16.68
15 /40	1.368	97.775	1.34413	95.423	0.00100	0.00100	val_loss	10.50	16.34
16 /40	1.270	98.372	1.31028	93.593	0.00100	0.00100	val_loss	2.52	17.56
17 /40	1.190	98.915	1.25076	92.906	0.00100	0.00100	val_loss	4.54	16.40
18 /40	1.124	98.969	1.13908	95.423	0.00100	0.00100	val_loss	8.93	16.59
19 /40	1.076	98.861	1.07834	96.796	0.00100	0.00100	val_loss	5.33	16.47
20 /40	1.009	99.023	1.00569	97.941	0.00100	0.00100	val_loss	6.74	16.44
21 /40	0.958	99.349	0.95493	98.169	0.00100	0.00100	val_loss	5.05	16.40
22 /40	0.918	99.132	0.91070	97.941	0.00100	0.00100	val_loss	4.63	16.63
23 /40	0.893	98.806	0.88666	98.169	0.00100	0.00100	val_loss	2.64	16.39
24 /40	0.848	98.698	0.84775	96.796	0.00100	0.00100	val_loss	4.39	17.68
25 /40	0.795	99.457	0.83075	95.881	0.00100	0.00100	val_loss	2.01	16.26
26 /40	0.763	99.078	0.76559	97.712	0.00100	0.00100	val_loss	7.84	17.57
27 /40	0.771	97.775	0.74434	98.169	0.00100	0.00100	val_loss	2.78	16.43
28 /40	0.716	99.078	0.72288	98.169	0.00100	0.00100	val_loss	2.88	16.48
29 /40	0.694	98.915	0.72327	97.025	0.00100	0.00050	val_loss	-0.05	16.40
30 /40	0.666	99.186	0.67769	97.941	0.00050	0.00050	val_loss	6.25	16.33
31 /40	0.656	99.295	0.66600	97.941	0.00050	0.00050	val_loss	1.72	16.35
32 /40	0.640	99.295	0.64988	98.398	0.00050	0.00050	val_loss	2.42	16.34
33 /40	0.622	99.674	0.63851	97.941	0.00050	0.00050	val_loss	1.75	16.53
34 /40	0.618	99.078	0.63537	97.254	0.00050	0.00050	val_loss	0.49	16.42
35 /40	0.601	99.512	0.62602	96.796	0.00050	0.00050	val_loss	1.47	16.71
36 /40	0.601	99.240	0.63942	96.568	0.00050	0.00025	val_loss	-2.14	16.32
37 /40	0.591	99.403	0.61240	97.712	0.00025	0.00025	val_loss	2.18	16.32
38 /40	0.573	99.729	0.60262	97.254	0.00025	0.00025	val_loss	1.60	16.44
39 /40	0.568	99.512	0.60843	96.339	0.00025	0.00013	val_loss	-0.96	16.38
40 /40	0.561	99.566	0.59764	97.025	0.00013	0.00013	val_loss	0.83	16.45

training elapsed time was 0.0 hours, 11.0 minutes, 58.32 seconds)

Fig. 5. Train with 40 epoch

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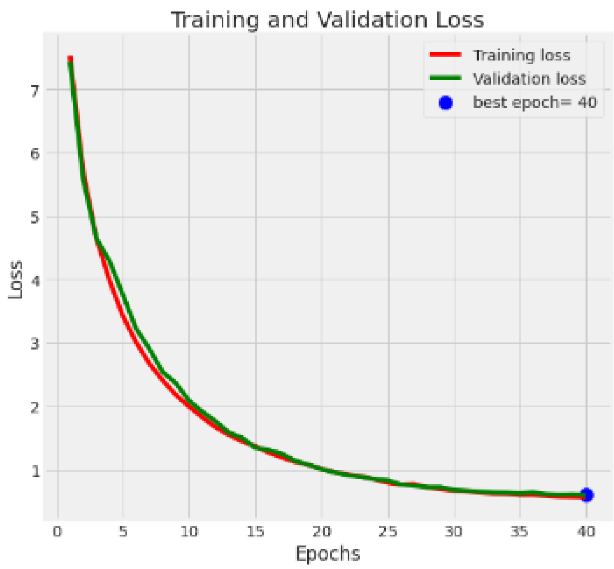

Fig. 6. Train and Validate Loss Plot

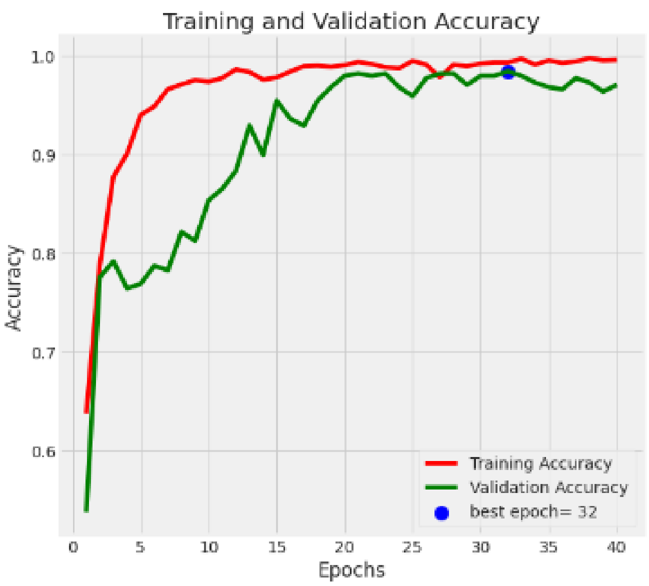

Fig. 7. Train and Validate Accuracy Plot

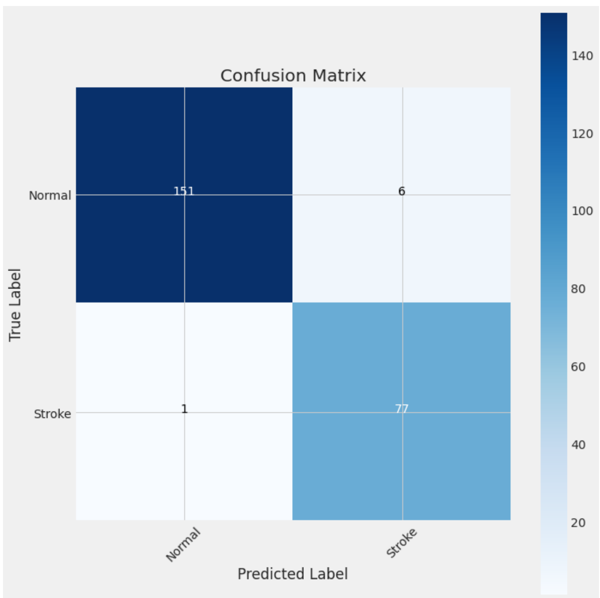

Fig. 8. Confusion Matrix

TABLE I. CLASSIFICATION PARAMETERS

Model	EfficientNetB0
Epoch	40
Accuracy	97%
Precision	96%
Recall	97%
F1-score	97%

As from the above table we can say that EfficientNetB0 based approach takes anatomical structures, tissue types, and tracer uptake features so getting high accuracy of 97%.

CONCLUSION

In conclusion, EfficientNetB0 has shown promising results for brain stroke classification on computed tomography scans. The model achieved high accuracy 97%, precision 96%, recall 97%, and F1-score 97% on the test set, indicating its ability to generalize well on unseen data. The data preprocessing and augmentation techniques helped in enhancing the features in the images and increasing the variability of the dataset, respectively. The fine-tuning of the EfficientNetB0 model for the specific task of brain stroke classification also contributed to its high performance.

In terms of future scope, exploring the use of transfer learning from pre-trained models such as ResNet, DenseNet, and Inception can help in achieving better performance with smaller datasets. Brain stroke diagnosis may be improved by combining MRI and PET scans, for example.

REFERENCES

[1] M. K. Reddy, K. Kovuri, J. Avanija, M. Sakthivel and S. Kaleru, "Brain Stroke Prediction Using Deep Learning: A CNN Approach," 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2022, pp. 775-780. doi: 10.1109/ICIRCA54612.2022.9985596

[2] J. Polson et al., "A Semi-Supervised Learning Framework to Leverage Proxy Information for Stroke MRI Analysis," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 2258-2261. doi: 10.1109/EMBC46164.2021.9631098

[3] B. R. Gaidhani, R. R.Rajamenakshi and S. Sonavane, "Brain Stroke Detection Using Convolutional Neural Network and Deep Learning Models," 2019 2nd International Conference on Intelligent Communication and Computational Techniques (ICCT), Jaipur, India, 2019, pp. 242-249. doi: 10.1109/ICCT46177.2019.8969052

[4] A. N. Tusher, M. S. Sadik and M. T. Islam, "Early Brain Stroke Prediction Using Machine Learning," 2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2022, pp. 1280-1284. doi: 10.1109/SMART55829.2022.10046889

[5] V. S. E and R. D, "A Systematic Method of Stroke Prediction Model based on Big Data and Machine Learning," 2022 Smart Technologies, Communication and Robotics (STCR), Sathyamangalam, India, 2022, pp. 1-5. doi: 10.1109/STCR55312.2022.10009283

[6] M. J. Carmel Mary Belinda, M. S. Devi, J. A. Pandian, R. K. Adurti and U. Kocherla, "Five layered Ensembled Deep Fully Connected Neural Network based Brain Stroke Prediction," 2022 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2022, pp. 199-202. doi: 10.1109/ICCCIS56430.2022.10037632

[7] N. Riz Kifli, H. Hidayat, Rahmawati, F. Putri Sukoco, A. Rahma Yuniarti and S. Rizal, "Brain Stroke Classification using One Dimensional Convolutional Neural Network," 2022 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bandung, Indonesia, 2022, pp. 1-6. doi: 10.1109/APWiMob56856.2022.10014207

[8] Y. Xu et al., "Deep Learning-Enhanced Internet of Medical Things to Analyze Brain CT Scans of Hemorrhagic Stroke Patients: A New

Authorized licensed use limited to: Instituto Federal da Paraiba (IFPB). Downloaded on February 14,2025 at 14:07:53 UTC from IEEE Xplore. Restrictions apply.

Approach," in IEEE Sensors Journal, vol. 21, no. 22, pp. 24941-24951, 15 Nov.15, 2021. doi: 10.1109/JSEN.2020.3032897

[9] V. Nedel'ko, R. Kozinets, A. Tulupov and V. Berikov, "Comparative Analysis of Deep Neural Network and Texture-Based Classifiers for Recognition of Acute Stroke using Non-Contrast CT Images," 2020 Ural Symposium on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT), Yekaterinburg, Russia, 2020, pp. 376-379. doi: 10.1109/USBEREIT48449.2020.9117784

[10] C. Rana, N. Chitre, B. Poyekar and P. Bide, "Stroke Prediction Using Smote-Tomek and Neural Network," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-5. doi: 10.1109/ICCCNT51525.2021.9579763

[11] S. Kumar and A. Sengupta, "EEG Classification For Stroke Detection Using Deep Learning Networks," 2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET), Patna, India, 2022, pp. 1-6. doi: 10.1109/ICEFEET51821.2022.9847883

[12] G. Garzón, S. Gomez, D. Mantilla and F. Martínez, "A deep CT to MRI unpaired translation that preserve ischemic stroke lesions," 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom, 2022, pp. 2708-2711. doi: 10.1109/EMBC48229.2022.9871154

[13] F. Aboudi, C. Drissi and T. Kraiem, "Efficient U-Net CNN with Data Augmentation for MRI Ischemic Stroke Brain Segmentation," 2022 8th International Conference on Control, Decision and Information Technologies (CoDIT), Istanbul, Turkey, 2022, pp. 724-728. doi: 10.1109/CoDIT55151.2022.9804030

[14] Z. B. Feliandra, S. Khadijah, M. F. Rachmadi and D. Chahyati, "Classification of Stroke and Non-Stroke Patients from Human Body Movements using Smartphone Videos and Deep Neural Networks," 2022 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, Indonesia, 2022, pp. 187-192. doi: 10.1109/ICACSIS56558.2022.9923501

[15] A. Tursynova, B. Omarov, K. Shuketayeva and M. Smagul, "Artificial Intelligence in Stroke Imaging," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2021, pp. 41-45. doi: 10.1109/Confluence51648.2021.9377102

[16] C. -L. Chin et al., "An automated early ischemic stroke detection system using CNN deep learning algorithm," 2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST), Taichung, Taiwan, 2017, pp. 368-372. doi: 10.1109/ICAwST.2017.8256481

[17] J. Yu, S. Park, S. -H. Kwon, K. -H. Cho and H. Lee, "AI-Based Stroke Disease Prediction System Using ECG and PPG Bio-Signals," in IEEE Access, vol. 10, pp. 43623-43638, 2022. doi: 10.1109/ACCESS.2022.3169284

[18] A. Tuladhar, S. Schimert, D. Rajashekar, H. C. Kniep, J. Fiehler and N. D. Forkert, "Automatic Segmentation of Stroke Lesions in Non-Contrast Computed Tomography Datasets With Convolutional Neural Networks," in IEEE Access, vol. 8, pp. 94871-94879, 2020. doi: 10.1109/ACCESS.2020.2995632.

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