Enhancing Acute Ischemic Stroke Diagnosis Using IoMT and Deep Learning Technologies

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***Abstract*—This paper introduces an alternative technique for diagnosing Acute Ischemic Stroke within the IoMT environment. In the proposed approach, the collected data is transmitted to a cloud-based center where the technique utilizes EfficientNet, a deep learning model, designed to extract features from MRI images thereby enhancing the detection of acute ischemic infarc-**

tions. The performance of EfficientNet is compared against two other models, CNN and MobileNet, demonstrating its superior efficacy through metrics such as accuracy, precision, recall, and F1-score, which stand at 92.31%, 92.28%, 92.33%, and 92.30%, respectively.

***Index Terms*—Acute Ischemic Stroke Diagnosis, Deep Learning, MobileNet, EfficientNet.**

I. INTRODUCTION

Stroke is a critical medical emergency that stands as the second primary cause of morbidity and mortality worldwide [1]. During stroke, some brain cells die because of occlusion of blood vessels [2]. In 2019, global stroke statistics showed 12.2 million new cases, 101 million prevalent cases, and 6.55 million deaths, making it the third principal contributor of disability on a global scale, and these are very worrying numbers [3]. Hemorrhagic and ischemic strokes are the main types of strokes, and ischemic strokes represent 85% of all stroke cases [4]. An acute ischemic stroke (AIS) can be defined as a loss of blood supply to brain cells suddenly, which leads to neurological disorders [5]. The manifestation of AIS encompasses sudden mouth and eye skewing, speech difficulties, aphasia, dysphagia, weakness, or numbness [6]. Predominantly, the etiology of AIS can be attributed to three pivotal factors: arteriosclerotic plaque formation within cerebral vessels and subsequent plaque rupture are responsible for about half of the occurrences; lacunar infarcts, stemming from small vessel disease, contribute to approximately 25%; and cardiogenic embolism is implicated in around 20% of cases [7].

Early and precise assessment of the existence of infarct lesions and their extent is imperative for clinicians to accurately classify stroke types and initiate appropriate treatment strategies [8]. Computed Tomography (CT) often serves as the initial diagnostic modality upon the suspicion of a stroke, with non-contrast CT scans being extensively employed for stroke diagnosis [9]. However, despite the numerous benefits of CT imaging, Magnetic Resonance Imaging (MRI) remains the superior diagnostic tool for AIS due to its enhanced sensitivity in detecting AIS lesions and its greater specificity in ascertaining the infarct size. Additionally, MRI offers the significant advantage of not exposing patients to ionizing radiation [10]. Variations in MRI sequences, particularly the Diffusion-Perfusion mismatch, are pivotal in elucidating the underlying mechanisms of stroke, thereby playing a critical role in the diagnostic process and guiding the selection of optimal treatment strategies [11]. Diffusion Weighted Imaging (DWI) and Apparent Diffusion Coefficient (ADC) mapping are recognized as the foremost techniques for the rapid detection of AIS following vascular obstruction, with AIS manifesting as hyperintense signals on DWI and hypointense signals on ADC mappings [11], [12].

Although modern technologies and tools currently in use are indispensable, they are often limited in responding with the speed and precision needed to minimize cerebral damage and death associated with stroke [13]. The reliance on manual interpretation of medical images by clinicians in many healthcare facilities worldwide introduces significant challenges, including: it is difficult to manually collect a large volume of high-quality stroke MRI scans. One of the biggest barriers we face in MRI screening is the time factor, and specifically, the analysis of brain MRI images is largely unexplored, representing a gap in the literature that our research seeks to fill by using the Internet of Medical Things (IoMT) and Artificial Intelligence (AI) to enhance the efficiency and effectiveness of stroke diagnosis and treatment.

The need to apply the features provided by IoMT technology, including high performance, reducing time, and saving the effort of both specialists and patients, has become necessary [14]. Within the framework of AIS management, IoMT can innovate state-of-the-art methods for collecting, using, and sharing medical data, reducing the period between the appearance of symptoms and the start of treatment [15]. With the increased interest in developing the smart medical system based on the services provided by the IoMT, systems have been built that link advanced sensors with insights based on AI. Through the integration of deep learning (DL) tools and IoMT innovation, we can accurately classify cells affected by acute ischemic infarction in brain images and diagnose them early.

However, while the potential benefits of IoMT and AI in enhancing AIS diagnosis are substantial, several challenges must be addressed for real-world implementation. First, expert acceptance is critical; healthcare professionals may exhibit resistance to adopting new technologies due to unfamiliarity or perceived complexity [16]. Effective training and user-friendly interfaces are essential to facilitate smooth integration into clinical workflows. Second, data privacy is a paramount concern, particularly when dealing with sensitive patient information [17]. Ensuring robust encryption and compliance with regulations like the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) is necessary to protect patient data and maintain trust. Lastly, technological constraints such as the need for high-speed internet connectivity, reliable infrastructure, and the interoperability of devices and platforms can hinder the widespread adoption of IoMT solutions in diverse healthcare settings.

By addressing these challenges, the proposed approach aims to improve the prediction of AIS in an IoMT environment, leveraging the DL technique to extract relevant features from AIS images and comparing its results with other models using real-world datasets.

The contribution of this paper can be summarized as follows:

- Propose an alternative AI technique to improve the prediction of AIS in an IoMT environment.
- Apply the EfficientNet as a DL technique to extract the relevant features from AIS images.
- Compare the results of EfficientNet with the other two models using real-world datasets.

The rest of this paper is organized as follows: Section 2 outlines our methodology, comparing three DL models: CNN, MobileNet, and EfficientNet. Section 3 presents the proposed framework that integrates the IoMT with our DL approach for AIS diagnosis. Section 4 discusses the experimental results, highlighting the superior performance of EfficientNet through key metrics. Finally, Section 5 concludes the paper by summarizing our findings and suggesting directions for future research in enhancing ischemic stroke diagnosis with IoMT and DL technologies.

II. METHODS

A. CNN

CNNs are more popular in the field of DL, especially in applications related to medical imaging [18]. They are an altered form of a fully connected multilayer feedforward neural network, designed to detect local characteristics for classification purposes. The basic architecture of a CNN includes an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. The most important layers in the CNN architecture are the convolutional layer and the pooling layer. The fundamental architecture of a CNN, specifically designed for medical image categorization, is shown in Figure 1. The number of neurons in the input layer, which processes the original images, matches the feature dimension input. Using a fixed step length, the convolution filters in the convolutional layer extract features from the image. To provide more information, each neuron in the convolutional layer is coupled by a set of weights to a specific part of the image in the previous layer. There is a local connection among the convolutional layer neurons.

The feature maps are obtained by extracting local features from the surface of the input layer. This allows the convolution filter of the current layer to effectively draw out the image's local features. To achieve feature extraction, the convolutional layer performs convolution operations by scanning the input data using its internal convolutional process. By capturing local features from the surface of the input layer, we can extract the feature maps. This enables the convolution filter of the current layer to actively pull out the local features of the image. Convolution operations are performed by the convolutional layer by checking the input data with its internal convolution process to carry out the feature extraction function.

$$X_j^i = f(\sum_{i \in M_j} X_i^{l-1} \times w_{ij}^l + b_j^l) \tag{1}$$

By decreasing the precision of the feature map, the pooling layer implements feature selection and information filtering to achieve spatial invariance. Pooling operations, such as max pooling and average pooling, reduce the number of parameters in the network and speed up the computation process by promptly minimizing matrix size. Through down-sampling of the input data, it can partially mitigate overlapping issues.

$$X_j^i = B_j^l \times d(X_i^{l-1}) + b_j^l) \tag{2}$$

Through the use of local category discrimination information, the application of the convolutional layer and pooling layer structure enables the achievement of image classification and identification tasks, thereby improving the flexibility of the network model.

The sample label space has been interpreted as the acquired 'distributed feature representation' by the fully connected layer. In addition, to improve the convolutional neural network's performance, the fully connected layer is followed by a ReLU activation function, which is commonly applied. Figure 1 shows the structure of the CNN model.

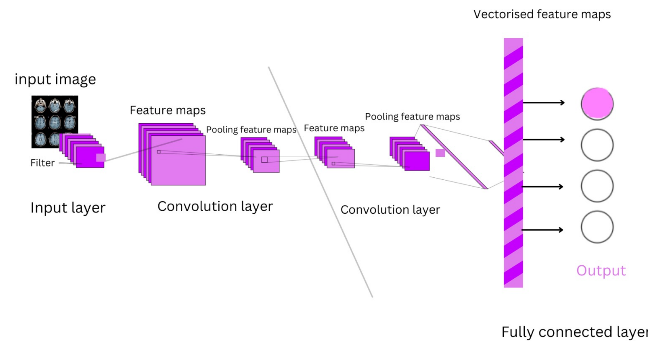


Fig. 1: Structure of CNN model.

B. MobileNet

To further enhance CNN architectures, techniques such as depth-wise separable convolution, exemplified by MobileNet [19], are employed, as illustrated in Figure 2. Depth-wise separable convolution decomposes traditional convolution into depth-wise and pointwise convolutions, thereby reducing the number of model parameters while maintaining accuracy and computational efficiency. Additionally, the use of dilated convolution in neural networks addresses the issue of limited receptive field size, enabling the learning of features at multiple scales and levels. By widening the receptive field of convolutional kernels, dilated convolution facilitates the extraction of global image features while maintaining spatial resolution and preserving global information. Additionally, the enhanced MobileNet model improves depth-wise separable convolution blocks by optimizing them with linear activation functions such as Sigmoid. This optimization helps retain in-channel information and enhance recognition and classification accuracy. The assessment of DL models involves using metrics like accuracy, sensitivity, and specificity to evaluate model performance in classification tasks. These metrics play a crucial role in determining the effectiveness of various algorithms and parameter configurations in handling classification tasks. In conclusion, advancements in CNN architectures like MobileNet, which incorporate techniques such as depth-wise separable convolution and dilated convolution, along with the use of effective evaluation metrics, significantly contribute to enhancing the accuracy and efficiency of medical image classification and recognition tasks.

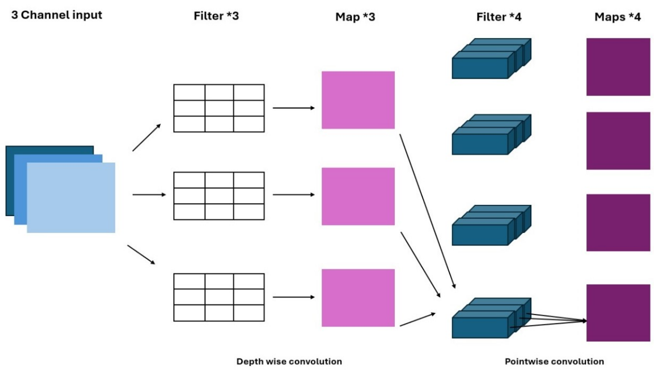


Fig. 2: Structure of the MobileNet.

C. EfficientNet

The goal of the developed EfficientNet model [20] is to provide a model scaling method that successfully strikes a balance between speed and accuracy (refer to Figure 3). Unlike other methods that focus on improving specific features like network depth, width, or image resolution, EfficientNet evaluates these characteristics and their connections. The authors offer a methodology to investigate the relationship between depth, width, resolution, and accuracy. They also acknowledge the mutual influence of these factors. For instance, the authors define each layer in the network as $Y_i = F_i(X_i)$, where X_i is the input tensor, Y_i is the output tensor, and F_i is the operator value, to help the reader recognize the problem. A more manageable representation of the network is made possible by describing N as a series of convolutional layers arranged into phases. The researchers use multiple constraints to decrease the amount of search space: they maintain the system's basic design and scale each component regularly while considering both processing and memory resources. Due to these constraints, the system's flexibility is reduced to expanding the initial network by the same amplification factor.

The researchers established a combination scaling method by conducting studies that modified a single dimension at each stage, as well as all dimensions at once. Using this method, a network's dimension, depth, and quality are all scaled using a combination factor, with specific variables determined by small grid searches. By employing the combined scalable technique, EfficientNet models (B1 through B7) were developed. Despite a significant increase in variables, EfficientNet-B3 was chosen for testing because it performed much better than B0. Additionally, EfficientNet demonstrated its superior power over the CNN network, while MobileNet, using the ImageNet dataset, showed substantial performance advantages.

III. PROPOSED MODEL

In this section, we outline the proposed methodology for integrating IoMT with DL techniques to enhance the diagnosis of AIS. While the IoMT framework is envisioned as a future integration, this methodology highlights the steps involved in leveraging DL within this context, as illustrated in Figure 4.

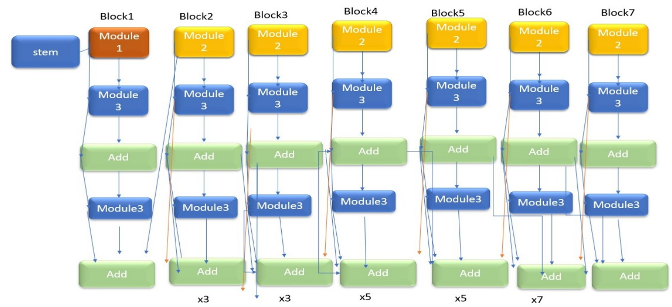


Fig. 3: Structure of the EfficientNet model.

The methodology involves several critical stages. The initial step involves collecting data using IoT devices, such as wearable sensors and imaging devices. These devices continuously monitor patients and gather real-time health data, including MRI images crucial for diagnosing AIS. The collected data is then transmitted to both the fog computing layer and the cloud computing layer. This dual-layer approach ensures that preliminary processing can occur close to the data source, reducing latency and bandwidth usage.

At the fog computing layer, preliminary data processing occurs. The trained model is deployed here to perform initial predictions on the collected AIS images. This helps in reducing the time complexity by providing quick, on-site diagnostic support. If the fog computing layer determines the image cannot be conclusively diagnosed, it forwards the data to the cloud computing layer for further analysis. In the cloud computing layer, a DL model is applied to extract relevant features from the dataset and identify AIS. The cloud layer performs more complex and resource-intensive computations, ensuring accurate and detailed analysis.

To ensure the reliability and effectiveness of the proposed model, a comprehensive validation process is implemented. The model is trained and validated using a large dataset of annotated MRI images, which includes both AIS-positive and AIS-negative cases. The dataset is divided into training and test sets, with 90% of the data used for training and 10% reserved for testing. This split ensures a robust evaluation framework.

The model's performance is evaluated using several key metrics, including accuracy, precision, recall, and F1-score. After validation by healthcare professionals, the model could be tested in the future using data from IoMT devices in a clinical setting. This step ensures the model's practical applicability and reliability in diagnosing AIS with the potential for future integration into an IoMT environment.

IV. EXPERIMENTAL RESULTS

A. Dataset Description

The dataset under investigation was acquired through diffusion MRI scans, approved by the Ethics Committee of the Turgut Özal University, Faculty of Medicine. It initially comprised 1,002 cases of AIS alongside 1,008 instances of healthy diffusion MR images. Subsequently, the dataset was expanded (termed Version 2) through the inclusion of

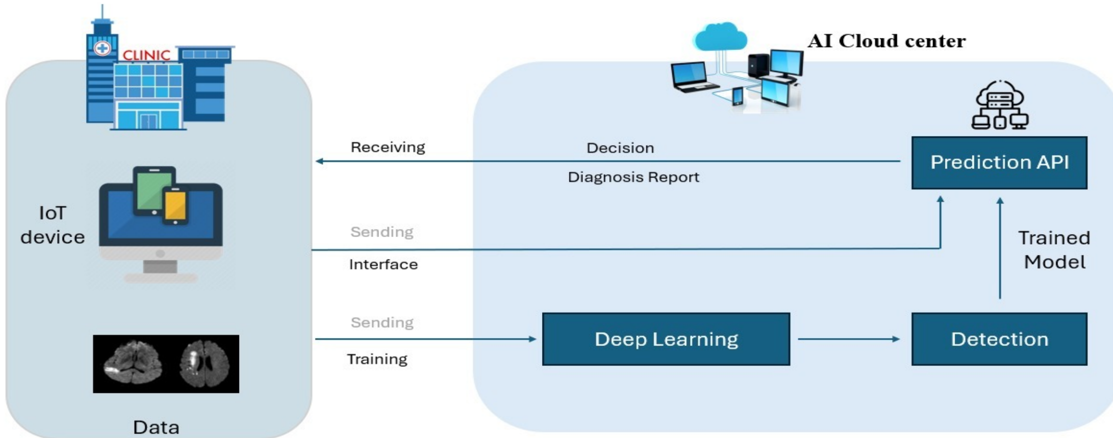


Fig. 4: The IoMT integrated deep learning Framework for AIS diagnosis and Decision-Making.

additional MRI images, culminating in a collection of 1,112 acute ischemic infarction and 1,202 normal diffusion MR images (https://www.kaggle.com/datasets/buraktaci/diffusion-mri-v2 (accessed on 5 February2024)) [21], [22]. This enhanced dataset was gathered from patients presenting to the neurology department of Turgut Özal University Medical Faculty Hospital in 2021, specifically those diagnosed with AIS. Illustrative samples of diffusion MR images are presented in Figure 5, while comprehensive patient information and dataset specifics are detailed in Table. I.

TABLE I: Properties of the collected dataset.

Diffusion MRIs	Male	Female	Total	Male Age	Female Age	Number of MRIs
AIS	38	46	84	74.4±14.7	71.21±15.14	1112
Healthy	25	20	45	69.2±8.54	72.6±14.41	1202

B. Results and Discussion

Within this section, the results of the developed model based on EfficientNet are compared with those of CNN and MobileNet. The parameters of these models are set according to their original implementations. The comparison results are given in Table II and Figure 6. From these results, we can see that the EfficientNet model has a high ability to predict AIS based on the performance measures. In general, it shows highly significant differences in terms of accuracy, precision, recall, and F1-score. For example, the difference between EfficientNet and CNN, and MobileNet based on accuracy is 17.95% and 23.93%, respectively. Based on the precision measure, the difference with CNN and MobileNet is 17.23% and 11.16%, respectively. In terms of the recall measure, the developed EfficientNet has a high recall value,

TABLE II: Comparison of Model Performance Metrics: Accuracy, Precision, Recall, and F1-score across Different Models.

Measure	CNN	MobileNet	EfficientNet
Accuracy	74.36%	68.38%	**92.31%**
Precision	75.05%	81.12%	**92.28%**
Recall	73.95%	66.96%	**92.33%**
F1-score	73.93%	63.70%	**92.30%**

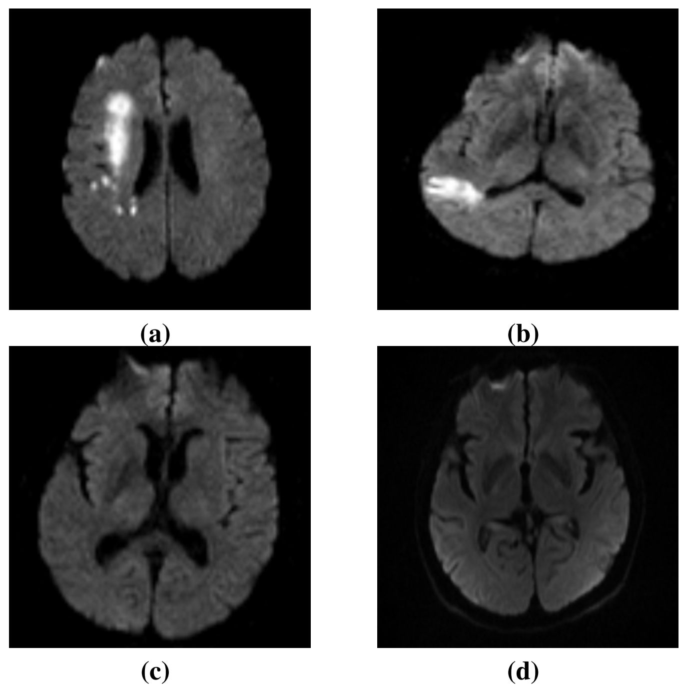


Fig. 5: Brain slices samples from the AIS dataset. (a) & (b) Two Ischemic Acute Infarction slices. (c) & (d) Two healthy brain Diffusion MRI slices.

TABLE III: Comparison of Diagnostic Accuracy Between the Proposed EfficientNet Method and Previous Studies.

Previous Studies	**Accuracy**
Jung & Whangbo [23]	71%
Pan et al. [24]	75.9%
Sahoo et al. [25]	83%
Cui et al. [26]	85%
Gautam & Raman [27]	86.11%
Wang et al. [28]	92%
Chin et al. [29]	92.97%
Proposed Methodology	**92.31%**

with the difference between it and CNN and MobileNet being nearly 18.38% and 25.37%, respectively. Regarding the F1-score value, the difference between EfficientNet and CNN, and MobileNet is nearly 18.37% and 28.6%, respectively. The same observation can be noted from Figure 6, which indicates the high ability of the developed model to detect AIS diagnosis in an IoMT environment.

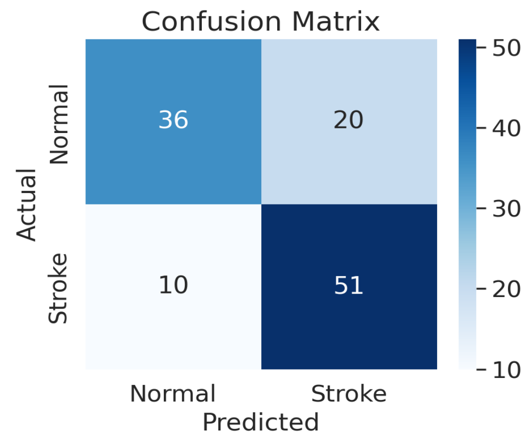
In addition to the above-discussed results, we present a comparison between the proposed method employing EfficientNet and previous studies in terms of accuracy.

The results in Table III provide a comprehensive comparison of our proposed method with previous studies. Our proposed methodology, with an accuracy of 92.31%, demonstrates substantial improvements over most previous studies. For instance, adaptive transfer learning [23] achieved an accuracy of 71%, and ResNet combined with a maximum a posteriori probability (MAP) [24] achieved 75.9%. Meanwhile, customized-VGG16 CNN [25], DeepSym-3D-CNN [26], and LG2P feature descriptor [27] achieved accuracies of 83%, 85%, and 86.11%, respectively. Notably, a DL-based algorithm [28] and CNN Algorithm [29] reported higher accuracies of 92% and 92.97%, respectively, which are close to the performance of our proposed method.

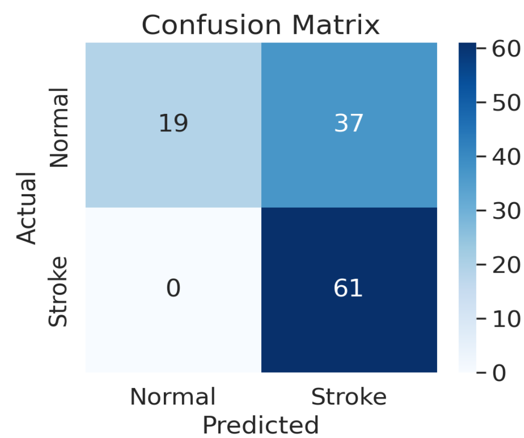
Overall, the comparison highlights the effectiveness and reliability of the EfficientNet model in diagnosing AIS within an IoMT environment. Our proposed method not only improves the diagnostic accuracy but also provides a robust framework for real-time health monitoring and data processing, ensuring timely and accurate medical intervention.

V. Conclusion

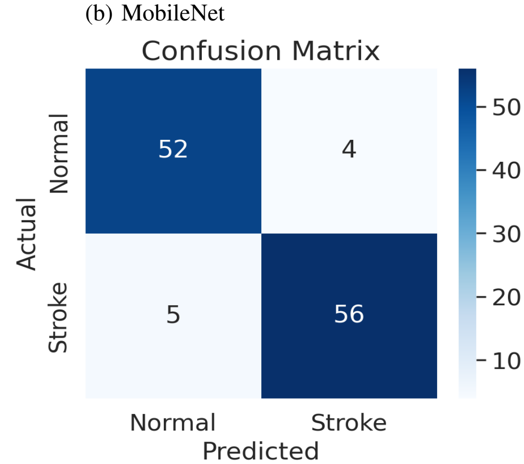
In our study, we investigated the integration of the IoMT with DL models to improve AIS diagnosis through MRI image analysis. Among the three DL models evaluated—CNN, MobileNet, and EfficientNet—EfficientNet emerged as the superior model, demonstrating the highest performance in accuracy, precision, recall, and F1-score. This indicates that EfficientNet, within an IoMT framework, significantly enhances AIS diagnostic processes by effectively analyzing MRI images for quicker and more accurate diagnosis. Our findings highlight the potential of leveraging IoMT and advanced DL



(a) CNN



(b) MobileNet



(c) EfficientNet

Fig. 6: Confusion Matrices of Different Models for AIS Prediction: (a) CNN, (b) MobileNet, and (c) EfficientNet.

technologies like EfficientNet to revolutionize healthcare, particularly in the timely and precise diagnosis of conditions such as AIS. Future work should focus on expanding the dataset for broader validation, incorporating real-time data processing with 6G technology, and integrating multimodal data sources to enhance diagnostic accuracy. Additionally, implementing user-friendly interfaces and ensuring compliance with data privacy regulations will be crucial for real-world applications.

REFERENCES

[1] D. Kuriakose and Z. Xiao, "Pathophysiology and treatment of stroke: present status and future perspectives," *International journal of molecular sciences*, vol. 21, no. 20, p. 7609, 2020.

[2] A. Subudhi, M. Dash, and S. Sabut, "Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 1, pp. 277–289, 2020.

[3] V. L. Feigin, B. A. Stark, C. O. Johnson, G. A. Roth, C. Bisignano, G. G. Abady, M. Abbasifard, M. Abbasi-Kangevari, F. Abd-Allah, V. Abedi *et al.*, "Global, regional, and national burden of stroke and its risk factors, 1990–2019: a systematic analysis for the global burden of disease study 2019," *The Lancet Neurology*, vol. 20, no. 10, pp. 795–820, 2021.

[4] A. Guzik and C. Bushnell, "Stroke epidemiology and risk factor management," *CONTINUUM: Lifelong Learning in Neurology*, vol. 23, no. 1, pp. 15–39, 2017.

[5] M. S. Phipps and C. A. Cronin, "Management of acute ischemic stroke," *Bmj*, vol. 368, 2020.

[6] Y. Yang, J. Yang, J. Feng, Y. Wang *et al.*, "Early diagnosis of acute ischemic stroke by brain computed tomography perfusion imaging combined with head and neck computed tomography angiography on deep learning algorithm," *Contrast Media & Molecular Imaging*, vol. 2022, 2022.

[7] Y. Zhao, X. Zhang, X. Chen, and Y. Wei, "Neuronal injuries in cerebral infarction and ischemic stroke: From mechanisms to treatment," *International journal of molecular medicine*, vol. 49, no. 2, pp. 1–9, 2022.

[8] S. K. Thiyagarajan and K. Murugan, "A systematic review on techniques adapted for segmentation and classification of ischemic stroke lesions from brain mr images," *Wireless Personal Communications*, vol. 118, no. 2, pp. 1225–1244, 2021.

[9] M. Nishio, S. Koyasu, S. Noguchi, T. Kiguchi, K. Nakatsu, T. Akasaka, H. Yamada, and K. Itoh, "Automatic detection of acute ischemic stroke using non-contrast computed tomography and two-stage deep learning model," *Computer Methods and Programs in Biomedicine*, vol. 196, p. 105711, 2020.

[10] K. Nael, R. Khan, G. Choudhary, A. Meshksar, P. Villablanca, J. Tay, K. Drake, B. M. Coull, and C. S. Kidwell, "Six-minute magnetic resonance imaging protocol for evaluation of acute ischemic stroke: pushing the boundaries," *Stroke*, vol. 45, no. 7, pp. 1985–1991, 2014.

[11] E. H. Tedyanto, K. Tini, and N. A. K. Pramana, "Magnetic resonance imaging in acute ischemic stroke," *Cureus*, vol. 14, no. 7, 2022.

[12] M. P. Lin and D. S. Liebeskind, "Imaging of ischemic stroke," *Continuum: Lifelong Learning in Neurology*, vol. 22, no. 5, pp. 1399–1423, 2016.

[13] B. Omarov, A. Tursynova, and M. Uzak, "Deep learning enhanced internet of medical things to analyze brain computed tomography images of stroke patients," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 8, 2023.

[14] A. Mabrouk, A. Dahou, M. Abd Elaziz, R. P. D. Redondo, and M. Kayed, "Medical image classification using transfer learning and chaos game optimization on the internet of medical things," *Computational Intelligence and Neuroscience*, vol. 2022, 2022.

[15] H. Son, S. Lee, K. Kim, K.-i. Koo, and C. H. Hwang, "Deep learning-based quantitative estimation of lymphedema-induced fibrosis using three-dimensional computed tomography images," *Scientific Reports*, vol. 12, no. 1, p. 15371, 2022.

[16] C. Longoni, A. Bonezzi, and C. K. Morewedge, "Resistance to medical artificial intelligence," *Journal of Consumer Research*, vol. 46, no. 4, pp. 629–650, 2019.

[17] W. Sun, Z. Cai, Y. Li, F. Liu, S. Fang, and G. Wang, "Security and privacy in the medical internet of things: a review," *Security and Communication Networks*, vol. 2018, pp. 1–9, 2018.

[18] H. Raja, M. U. Akram, A. Shaukat, S. A. Khan, N. Alghamdi, S. G. Khawaja, and N. Nazir, "Extraction of retinal layers through convolution neural network (cnn) in an oct image for glaucoma diagnosis," *Journal of Digital Imaging*, vol. 33, pp. 1428–1442, 2020.

[19] W. Sae-Lim, W. Wettayaprasit, and P. Aiyarak, "Convolutional neural networks using mobilenet for skin lesion classification," in *2019 16th international joint conference on computer science and software engineering (JCSSE)*. IEEE, 2019, pp. 242–247.

[20] D. Ghimire, D. Kil, and S.-h. Kim, "A survey on efficient convolutional neural networks and hardware acceleration," *Electronics*, vol. 11, no. 6, p. 945, 2022.

[21] B. Tasci, "Automated ischemic acute infarction detection using pre-trained cnn models' deep features," *Biomedical Signal Processing and Control*, vol. 82, p. 104603, 2023.

[22] B. Tasci and I. Tasci, "Deep feature extraction based brain image classification model using preprocessed images: Pdrnet," *Biomedical Signal Processing and Control*, vol. 78, p. 103948, 2022.

[23] C.-L. Chin, B.-J. Lin, G.-R. Wu, T.-C. Weng, C.-S. Yang, R.-C. Su, and Y.-J. Pan, "An automated early ischemic stroke detection system using cnn deep learning algorithm," in *2017 IEEE 8th International conference on awareness science and technology (iCAST)*. IEEE, 2017, pp. 368–372.

[24] L. Cui, S. Han, S. Qi, Y. Duan, Y. Kang, and Y. Luo, "Deep symmetric three-dimensional convolutional neural networks for identifying acute ischemic stroke via diffusion-weighted images," *Journal of X-ray science and technology*, vol. 29, no. 4, pp. 551–566, 2021.

[25] A. Gautam and B. Raman, "Local gradient of gradient pattern: a robust image descriptor for the classification of brain strokes from computed tomography images," *Pattern Analysis and Applications*, vol. 23, pp. 797–817, 2020.

[26] S.-M. Jung and T.-K. Whangbo, "A deep learning system for diagnosing ischemic stroke by applying adaptive transfer learning," *Journal of Internet Technology*, vol. 21, no. 7, pp. 1957–1968, 2020.

[27] J. Pan, G. Wu, J. Yu, D. Geng, J. Zhang, and Y. Wang, "Detecting the early infarct core on non-contrast ct images with a deep learning residual network," *Journal of Stroke and Cerebrovascular Diseases*, vol. 30, no. 6, p. 105752, 2021.

[28] P. K. Sahoo, S. Mohapatra, C.-Y. Wu, K.-L. Huang, T.-Y. Chang, and T.-H. Lee, "Automatic identification of early ischemic lesions on non-contrast ct with deep learning approach," *Scientific Reports*, vol. 12, no. 1, p. 18054, 2022.

[29] K. Wang, Q. Shou, S. J. Ma, D. Liebeskind, X. J. Qiao, J. Saver, N. Salamon, H. Kim, Y. Yu, Y. Xie *et al.*, "Deep learning detection of penumbral tissue on arterial spin labeling in stroke," *Stroke*, vol. 51, no. 2, pp. 489–497, 2020.