Revolutionizing Neurological Diagnostics: Integrating 6G Technology with Deep Learning for Enhanced Detection of Multiple Sclerosis and Myelitis

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***Abstract*—This paper proposes an alternative detection framework for multiple sclerosis (MS) and idiopathic acute transverse myelitis (ATM) within the 6G-enabled Internet of Medical Things (IoMT) environment. The developed framework relies on the implementation of a deep learning technique known as Dense Convolutional Networks (DenseNets) in the 6G-enabled IoMT to enhance prediction performance. To validate the performance of DenseNets, we compared it with other deep learning techniques, including Convolutional Neural Networks (CNN) and MobileNet, using real-world datasets. The experimental results show the high performance of DenseNets in predicting MS and ATM compared to other methods, achieving an accuracy of nearly 90%.**

***Index Terms*—6G networks; Internet of medical things; deep learning; Multiple Sclerosis and Myelitis.**

I. Introduction

Acute myelopathies encompass a diverse set of neurological disorders marked by rapid onset spinal cord dysfunction stemming from various causes, leading to significant acute and potential long-term disability. These disorders are categorized by their symptom onset speed and deterioration rate, with inflammatory myelopathies appearing suddenly within days, and hereditary types evolving over months, although some chronic forms can acutely worsen [1]. The severity and outcomes depend on the nature and extent of spinal cord damage, with distinct subtypes including inflammatory myelopathies like multiple sclerosis (MS), idiopathic acute transverse myelitis (ATM), autoantibodies against aquaporin-4 (AQP4-IgG), and myelin oligodendrocyte glycoprotein (MOG-IgG) each with specific characteristics and implications for diagnosis and treatment [2]. Distinguishing among the diverse types of myelopathies—whether they stem from inflammatory, infectious, or demyelinating origins—presents a challenge but is crucial for initiating timely and appropriate treatment while preventing harm caused by unnecessary procedures [3]. In 2002, the Transverse Myelitis Consortium Working Group (TMCWG) established diagnostic criteria for ATM, emphasizing the need for clinical evidence of spinal cord dysfunction, neuroimaging to rule out structural causes, and proof of inflammation through MRI or cerebrospinal fluid (CSF) analysis, among other exclusions, to classify a case as definite or possible ATM [4]. However, even with these strict guidelines, a relatively small percentage of patients are diagnosed as having ATM, and some initially diagnosed patients may later receive different diagnoses, reflecting challenges in accurately identifying this condition [5], [6].

Diagnosing acute myelopathy begins with a comprehensive neurological evaluation to identify the affected spinal cord region, followed by Magnetic resonance Imaging (MRI) to investigate compressive or structural causes. MRI with gadolinium contrast is the preferred method [7]. ATM typically shows a central T2 hyperintense lesion extending over more than two spinal segments and occupying more than two-thirds of the cord's cross-sectional area, often with variable enhancement patterns [8]. On the other hand, MS features smaller spinal lesions, usually affecting less than two segments and often located dorsolaterally, with T2 hyperintensity and contrast enhancement [8]. MS lesions demonstrate a pattern of dissemination in time and space, with the presence of oligoclonal bands in CSF further supporting the diagnosis [9], distinguishing it from ATM through imaging and clinical follow-up.

Despite high sensitivity, MRI may not always definitively differentiate between MS and ATM due to overlapping imaging features necessitating supplementary invasive procedures like CSF analysis for conclusive diagnosis. Approximately 40% of acute transverse myelopathies may remain undemonstrated on MRI, and no clearly different and specific patterns have been conclusively identified for each etiology [10], [11]. This diagnostic ambiguity not only complicates clinical decision-making but also delays the initiation of appropriate treatment regimes, highlighting the imperative need for innovative diagnostic approaches.

Recently, Artificial Intelligence (AI) has emerged as a promising adjunct by potentially enhancing the specificity and sensitivity of MRI interpretations, thereby facilitating early and accurate differentiation of these conditions [12], [13]. Additionally, the large quantity of data generated quickly at a short timescale, raises the problem of efficiently processing such images in real-time to help the medical field detect these diseases in their early stages. So, the integration of sixth-generation (6G) communication solutions with AI heralds a transformative leap in the diagnostic precision and management of neurological conditions. This synergy promises to overcome the limitations of MRI in distinguishing these disorders by enabling real-time, high-speed data transmission and advanced AI analytics. The high bandwidth and ultra-low latency characteristic of 6G facilitate the seamless transfer of large volumes of imaging data, enhancing the capabilities of AI algorithms in processing and analyzing MRI scans with unprecedented speed and accuracy [14]–[16]. This technological advancement not only aids in the early and accurate differentiation of acute myelopathies but also supports telemedicine applications, allowing neurologists to deliver timely, informed, and personalized patient care.

Little research has focused on differentiating MS from its mimics, such as Neuromyelitis Optica Spectrum Disorder (NMOSD). For example, Yoo et al. [17] introduced a hierarchical multimodal fusion (HMF) deep learning (DL) model to distinguish NMOSD from MS using MRI and diffusion tensor images, achieving an 81.3% diagnostic accuracy. Similarly, Wang et al. [18] developed a DL model using 2D CNNs with transfer learning to differentiate NMOSD from MS in MRI images, outperforming traditional 3D CNN models with higher accuracy, sensitivity, and specificity over 70%. Another study by Eshaghi et al. [19] used multi-kernel learning for the automatic diagnosis of NMO and MS, achieving an 88% accuracy in differentiating NMO from MS and 84% accuracy in distinguishing between NMO, MS, and healthy controls. Despite these advancements, the diagnostic accuracy remains relatively low. To the best of our knowledge, only one study has presented a model specifically for classifying MS from ATM.

The economic feasibility and scalability of deploying a 6G-

AI diagnostic system for neurological conditions are crucial, particularly in resource-limited settings. High initial investments for infrastructure and ongoing operational costs must be considered. The proposed solution leverages fog computing to reduce costs and latency. A phased deployment approach, starting in critical regions, can help manage expenses. Overall, the economic benefits, such as improved patient outcomes and reduced invasive procedures, must be carefully evaluated.

In this paper, we proposed DL technique to enhance the prediction of MS and ATM. In general, the data is collected using devices and will be sent to Fog computing in a 6G network that will pass the data to the cloud computing layer. Within this layer, the DL model is learned using the collected data and then we will distribute the model to preserve it at the fog computing layer. This will reduce the transmission cost and can support the way area without a sufficient number of doctors.

The main contribution of this study can be summarized as follows:

1) Propose an alternative Neurological Diagnostics Framework in 6G IoMT environment to enhance the prediction of MS and ATM.
2) Apply Densnet as a DL technique to predict the prediction of MS and ATM.
3) Apply the developed model to the real-world and compare it with other DL models.

The remainder of this paper is structured as follows: Section 2 outlines our methodological approach by comparing three DL models: Convolutional Neural Networks (CNNs), MobileNet, and Dense Convolutional Networks (DenseNets), thereby laying the groundwork for our computational strategy. In Section 3, we introduce our proposed framework that merges the 6G IoMT with our DL techniques to improve the diagnosis of MS and ATM, illustrating the synergistic potential of advanced technologies in healthcare. Section 4 delves into the results of our experiments, underscoring DenseNet's outstanding accuracy in diagnosing MS and ATM, which in turn confirms our framework's efficacy. Concluding the paper, Section 5 recaps our main contributions and explores future research avenues, particularly the expansion of our 6G-IoMT model to diagnose additional neurological conditions, ensuring clarity and conciseness while enhancing overall readability.

II. METHODS

Within this section, we introduce basic information about CNN, MobileNet, and DenseNet as DL techniques.

A. CNN

In the field of DL, CNNs are widely used, especially for applications involving medical imaging [20]. For division neural networks, it's an amended version of a fully connected multilayer feed, aimed at identifying local peculiarities to classify them. The basic architecture of a CNN includes the input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The convolutional layer and pooling layer are the major components in the CNN architecture. The basic CNN architecture, designed particularly for medical image classification, is shown in Figure 1. The original images, set up by several neurons in the input layer, correspond to the feature dimension input. The convolution filters in the convolutional layer extract features from the image using a fixed step length. Additionally, each neuron in the convolutional layer is connected to a group of weights to a specific part of the image in the top layer. Among the neurons in the convolutional layer, there is a local connection. By obtaining local features from the surface of the input layer, feature maps are easily created. This effective extraction of local image features enables the convolutional filter of the current layer to function efficiently. To achieve the feature extraction function, the convolutional layer performs convolution operations by inspecting the input data using its internal convolution process. Extracting local features from the input layer's surface allows for the creation of feature maps, which in turn enables the current layer's convolution filter to effectively capture local image features. The convolutional layer performs convolution operations by examining the input data with its internal convolution process to carry out the feature extraction function.

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

To achieve spatial invariance, the pooling layer performs feature selection and information filtering by decreasing the resolution of the feature map. Rapidly reducing the matrix size, pooling operations like max pooling and average pooling decrease the network's parameters and accelerate computation. Additionally, downsampling the input data helps mitigate overlapping issues.

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

The flexibility of the network model is enhanced by facilitating the completion of image categorization and recognition tasks through the use of convolutional layers, pooling layers, and local category discrimination information. The fully connected layer transforms the sample label space into the obtained 'distributed feature representation.' Moreover, the commonly applied ReLU activation function follows the fully connected layer to enhance the performance of convolutional neural networks.

B. MobileNet

Algorithms like depth-wise separable convolution, as described by MobileNet [21], are used to further strengthen CNN designs, as shown in Figure 2. Depth-wise separable convolution reduces the total number of parameters needed for the model without losing computational performance or accuracy by breaking down traditional convolution into depth-wise and point-wise convolution. Additionally, the problem of limited receptive field size can be addressed by using dilation convolution in neural networks, which allows the learning of characteristics at multiple scales and levels. Increased

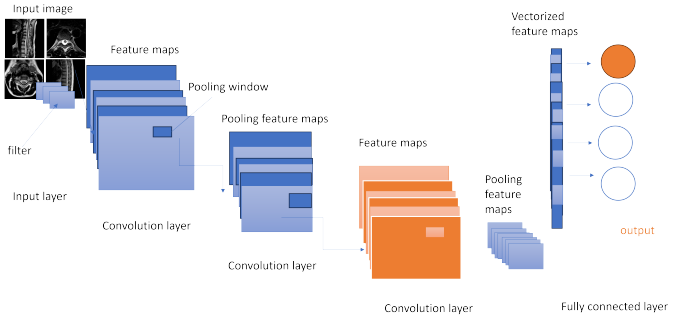


Fig. 1: Structure of CNN model.

computation enhances the ability to extract intrinsic image features while maintaining spatial resolution and global data by expanding the receptive field of convolutional kernels. Furthermore, by employing linear algebra operations like the Sigmoid function, the enhanced MobileNet model improves depth-wise separable convolutional blocks. This enhancement aids in preserving channel data and improves classification and recognition precision. When assessing the performance of DL models in tasks such as classification, variables like accuracy, sensitivity, and specificity are applied. These measures are essential for determining how well various algorithms and variable options perform categorization tasks. In summary, modifications in CNN design, such as MobileNet—which combines techniques like dilation convolution and depth-wise separable convolution—along with the application of effective evaluation metrics, have a significant positive impact on improving the accuracy and efficiency of medical image categorization and recognition applications.

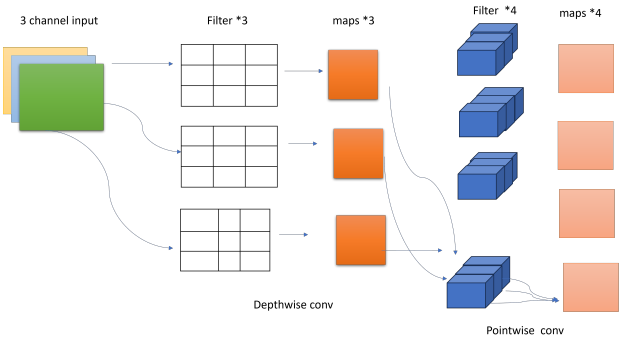


Fig. 2: Structure of the MobileNet.

C. Dense Convolutional Networks (DenseNets)

DenseNets [22] are characterized by their densely connected architecture. Unlike standard CNNs, which usually consist of sequentially stacked layers, DenseNets have a more complex design.

In general, the fundamental unit in DenseNets is the dense block. Each dense block comprises multiple convolutional layers stacked together (see Figure 3). Crucially, every layer within a dense block receives feature maps from all preceding layers within the same block. The feature maps from different layers are concatenated along the channel dimension. This design choice encourages feature reuse and facilitates the flow of information across layers. By directly connecting each layer to all subsequent layers, DenseNets mitigate the vanishing-gradient problem, allowing gradients to flow more effectively during backpropagation.

Transition layers serve as connectors between dense blocks. They consist of (1) Batch Normalization Layer: Normalizes feature maps to stabilize training. (2) 1x1 Convolutional Layer: Reduces the number of channels, controlling computational complexity. (3) Average Pooling: Reduces spatial dimensions while preserving essential information.

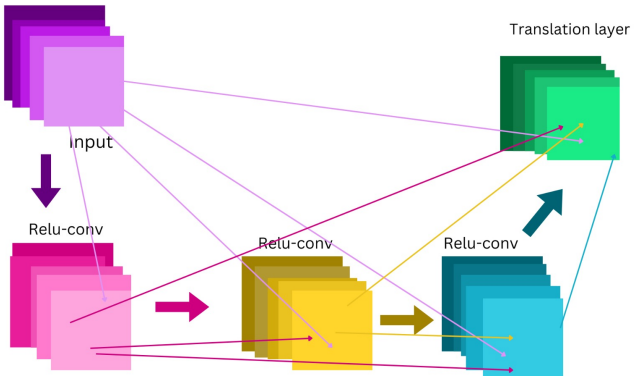


Fig. 3: Structure of basic DenseNet.

III. Proposed Model 6G IoMT Framework

In this section, we present a detailed methodology of the developed 6G IoMT Framework for the detection of MS and ATM. This framework leverages DenseNets and integrates them within a 6G-enabled IoMT environment to enhance prediction performance. The proposed framework is illustrated in Figure 4.

The first step in our methodology involves data collection. Medical images of MS and ATM are acquired from medical imaging devices. These images are then processed at the edge computing layer, which includes fog computing and Multi-access Edge Computing (MEC) servers. This layer performs preliminary computations, reducing latency and bandwidth usage. Aggregated data from various edge devices are subsequently transmitted to the cloud computing layer through the 6G network. In the cloud computing layer, the DenseNet model is trained using the medical images. Once trained, the DenseNet model is deployed back to the fog computing layer to enable real-time predictions. Medical professionals can use the deployed model to perform diagnostics on new medical images, receiving predictions with high accuracy.

Additionally, our model offers another service: if an expert aims to predict the outcome for a current patient, the test pattern in the API forecasting tools is used. By leveraging both fog and cloud computing, the framework ensures efficient data transmission and facilitates model deployment across diverse healthcare settings.

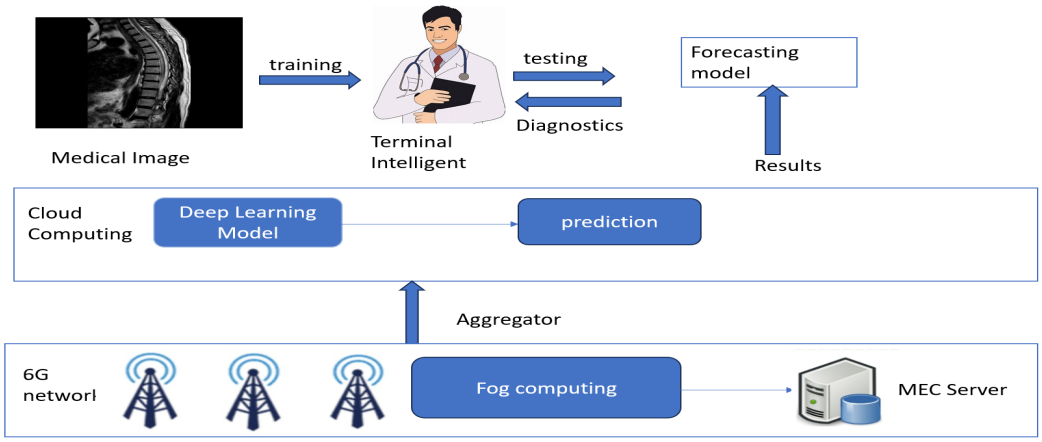


Fig. 4: The suggested 6G-enabled IoMT framework diagram.

The model's performance is evaluated using metrics such as accuracy, F1-score, precision, and recall to ensure its reliability in clinical settings. The framework also includes a forecasting and continuous learning component. Diagnostic results are integrated with forecasting models to predict the progression of MS and ATM. The model is continuously updated with new data to improve its diagnostic capabilities over time.

While the proposed 6G IoMT Framework is currently conceptual, its future implementation will involve real-world testing and validation to refine the integration of 6G technology with DL models in medical diagnostics.

IV. EXPERIMENTAL RESULTS

A. Dataset Description

This study utilized a novel dataset of 2,746 MR images, approved by Fırat University's Ethics Committee, featuring patients with myelitis but not MS, MS patients, and healthy controls. The myelitis cases showed lesions exceeding three vertebral lengths, while MS lesions were generally shorter than two vertebral segments and located posterolaterally. The control group exhibited no spinal lesions. Due to lesion size variability, the number of images per subject varied, with 4 to 6 images for sagittal views and 6 to 10 for axial views, as depicted in Fig. 5. The dataset, stored in JPG format and detailed further in Table. I, includes 150 healthy controls, 128 MS patients, and 131 myelitis patients, segmented in both axial and sagittal planes for analysis. This valuable dataset is accessible for research purposes at (https://www.kaggle.com/datasets/turkertuncer/myelitis3classes (accessed on 13 March 2024)) [13].

TABLE I: Properties of the collected dataset.

Class	Male	Female	Total	Age (Mean ± sd)	Number of MRIs
Myelitis	63	68	131	35.7±5.22	667
MS	55	73	128	33.4±6.24	706
Control	75	75	150	34.4±3.16	1373

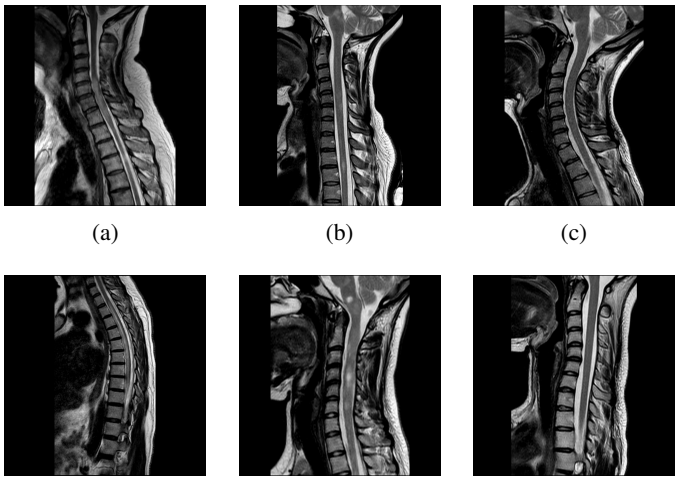


Fig. 5: Sample slices from the collected dataset, demonstrating typical features in each category. (a), (d) Myelitis; (b), (e) Multiple Sclerosis (MS); (c), (f) Control group.

B. Results and Discussion

In this section, we discuss the performance comparison of the DenseNet model with other DL techniques, specifically CNN and MobileNet, based on key metrics: accuracy, precision, recall, and F1-score. The implementation of those DL techniques is determined based on the original references. Table II presents the detailed performance metrics for each model.

From those results, we can observe that the DenseNet model outperformed both CNN and MobileNet across all evaluated metrics. The accuracy of DenseNet reached 90.22%, which is notably higher than CNN's 82.97% and MobileNet's 88.77%. This indicates that DenseNet provides a more reliable prediction for diagnosing MS and ATM. Similarly, in terms of precision, DenseNet achieved 88.84%, compared to CNN's 80.99% and MobileNet's 88.25%. Higher precision suggests

that DenseNet is more effective in correctly identifying true positive cases, reducing the likelihood of false positives. The recall metric, which measures the ability of the model to identify all relevant cases, also favored DenseNet with a value of 88.61%. In comparison, CNN and MobileNet achieved 81.16% and 87.45%, respectively. This higher recall value for DenseNet indicates its superior sensitivity in detecting actual positive cases of MS and ATM. Finally, the F1-score, which provides a balance between precision and recall, was highest for DenseNet at 88.72%, while CNN and MobileNet scored 81.08% and 87.82%, respectively. This further confirms DenseNet's robust performance in predicting these neurological conditions.

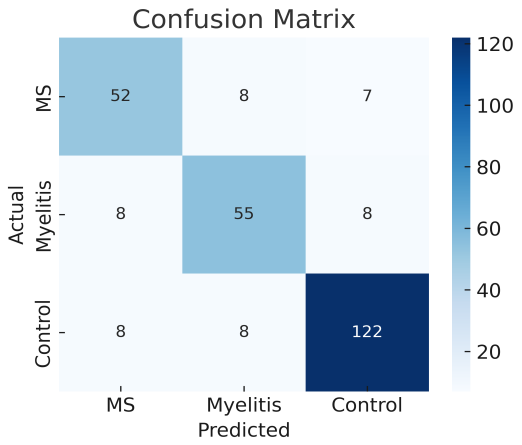
Examining the confusion matrices for each model, as illustrated in Figure 6, provides a more detailed understanding of their classification performance. The confusion matrices reveal that DenseNet significantly reduces misclassifications compared to CNN and MobileNet, leading to higher precision, recall, and overall accuracy.

TABLE II: Performance Metrics Comparison of CNN, MobileNet, and DenseNet Models in Diagnosing MS and ATM

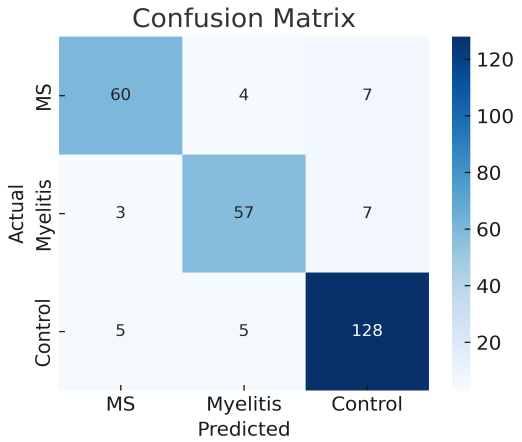
Measure	CNN	MobileNet	DenseNet
Accuracy	82.97%	88.77%	**90.22%**
Precision	80.99%	88.25%	**88.84%**
Recall	81.16%	87.45%	**88.61%**
F1-score	81.08%	87.82%	**88.72%**

To further contextualize our findings, we compared the performance of our proposed methodology with previous studies, as shown in Table III. This comparison highlights the significant improvements our approach offers over past methodologies. For instance, 3D CNN [23] achieved an accuracy of 71.1%, and the hierarchical multimodal fusion model [17] reached 81%. Gray matter volumes with random forest [24] showed an accuracy of 80%, while the multi-kernel learning model [19] achieved 84%. Our DenseNet-based approach not only outperformed these studies but also consistently provided higher accuracy across different evaluation metrics. This underscores the value of integrating 6G technology with advanced DL models in the IoMT framework for neurological diagnostics.

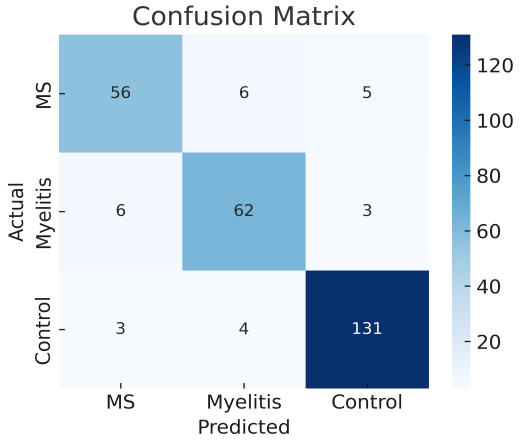
Overall, the superior performance of DenseNet across all metrics, coupled with its highest accuracy compared to previous studies, demonstrates its potential effectiveness for future integration in a 6G-enabled IoMT environment for detecting MS and ATM. Although we have not yet integrated the 6G-enabled IoMT environment with our model, our results suggest that such an integration could enable faster and more accurate diagnostics, which are crucial for timely and appropriate treatment interventions. These results validate the potential of our proposed framework to revolutionize neurological diagnostics, providing a strong foundation for future research and development in this area.



(a) CNN



(b) MobileNet



(c) DenseNet

Fig. 6: Confusion matrices of the models: (a) CNN, (b) MobileNet, and (c) DenseNet, showcasing the classification performance and misclassifications for each model.

TABLE III: Comparison of Accuracy Between Previous Studies and the Proposed DenseNet-Based Methodology for Neurological Diagnostics.

Previous Studies	Accuracy
Kim et al. [23]	71.1%
Yoo et al. [17]	81%
Wang et al. [18]	75%
Eshaghi et al. [24]	80%
Eshaghi et al [19]	84%
Amin et al. [25]	78%
Huang et al. [26]	81.4%
Seok et al. [12]	76.1%
Proposed Methodology	**90.22%**

V. Conclusion and future works

In this paper, we developed an alternative neurological diagnostic technique for the detection of MS and ATM within the 6G network. The developed model depends on applying the DenseNet model to enhance the prediction process. To validate the performance of the developed model, a set of real-world datasets was used. Additionally, we conducted comparisons with other DL techniques, namely CNN and MobileNet. From the results, the DenseNet has established its performance among the other techniques.

Besides the promising results, we can extend the developed model's neurological diagnostic technique in a 6G-IoMT environment to other diseases.

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