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RESEARCH ARTICLE

Transfer Learning and Hybrid Deep Convolutional Neural Networks Models for Autism Spectrum Disorder Classification From EEG Signals

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ABSTRACT Autism spectrum disorder (ASD) is a developmental disease characterised by restricted and repetitive behaviours, as well as difficulty in social communication and interaction, in children. The clinical diagnosis of ASD is reached by behavioural screening, which delays early intervention. Electroencephalography (EEG) is a method for analysing the brain's electrical activity that has proven useful in the diagnosis of several neurological illnesses. Pre-trained deep Convolutional Neural Networks (CNNs) were used to extract features from the spectral profiles of the EEG dataset and classify patients into mild, moderate, and severe patients, as well as age-matched control subjects. Accordingly, the primary goal of this study is to use the pre-trained CNNs as classifiers in order to reap the benefits of transfer learning, and the secondary goal is to propose a hybrid model by employing decision tree (DT), K nearest neighbour (KNN), and a Support Vector Machine (SVM) machine learning classification techniques to categorise the features of the pre-trained CNN networks into mild, moderate, severe, and normal categories. The results show that using SqueezeNet for transfer learning improves classification accuracy to 85.5%, and that using SqueezeNet for hybrid models improves classification accuracy to 87.8% using SVM. Therefore, a hybrid model based on the combination of SqueezeNet and SVM might be utilised to automatically diagnose ASD based on the individual's EEG data.

INDEX TERMS Autism, EEG, deep learning, transfer learning, convolutional neural networks, machine learning.

I. INTRODUCTION

Autism spectrum disorders (ASD) are neurodevelopmental illnesses characterized by markedly aberrant social interaction, impaired communication and language skills, and narrow interests [1]. Symptoms occur throughout childhood or infancy and are usually followed by a continuous course with no recovery from an illness [2]. Symptoms appear after the age of six months, become established by the age of two or three years old, and remain into adulthood, but with less

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severity [3], [4]. The 'spectrum' in ASD is for indicating that autistic individuals can have a multitude of symptoms, such as difficulties in motor movement abilities, limited attention spans, and sleep and gastrointestinal disturbances [2]. These are some prevalent characteristics of children with autism in which frequently, autistic children have communication difficulties, like refusing to engage in conversation, being unable to use appropriate language, repeating what they hear, and having a low linguistic understanding [5], [6]. However, some experience sensory disturbances, as well. These disturbances might be auditory, visual, tactile, gustatory, vestibular, or proprioceptive. Additionally, they avoid social interaction, as they prefer to be alone, the majority avoid making eye contact with others and lack the capacity to receive affection from those closest to them [7].

When a child is screened early, the problem is found and treated faster and better. The sooner a trained diagnostic team can confirm the diagnosis, the sooner any needed treatment can start [7]. Research suggests that there is a higher prevalence of autism in males compared to females. The prevalence of autism has a male-to-female ratio of 4-to-1 [7].

Indeed, ASD is a complex disorder and its symptoms overlap with other psychiatric disorders. So, it is important to use the appropriate assessment scales to diagnose subjects with ASD [8]. Numerous assessments can be employed to ascertain the presence or absence of autism in children, such as behavioral evaluation and screening for occupational therapy, among others [9]. Several widely used clinical procedures for assessing autism spectrum disorder include the Childhood Autism Rating Scale (CARS) [10], Autism Diagnostic Observation Schedule (ADOS) [11] and Autism Diagnostic Interview-Revised (ADI-R) [12]. Nevertheless, it is important to acknowledge that each of these assessments have distinct advantages and limitations. These assessments are characterized by their time-intensive nature, extensive questions, and the necessity of licensed specialists for their administration [9], [13].

This illustrates that autism diagnosis requires scientific improvements and support, therefore, early autism diagnosis requires clinical signs or biomarkers as clinical assessments alone cannot diagnose early [14], [15], [16]. One of the most essential indications for diagnosing ASD is the electroencephalogram (EEG). EEG signals contain a wealth of information about the brain neural activities [17], [18], [19], [20], [21].

EEG with machine learning, deep learning, and other advanced computing technologies can be used to diagnose and educate children early [9], [22]. Many researchers across the world are currently attempting to use neuroscience to treat and identify children with ASD, and the study and classification of EEG patterns can greatly aid in the diagnosis of a patient [9].

EEG waveforms were reported in autism and control patients, particularly the gamma band in the frontal brain lobe which can be discriminated between ASD and control patients early in the first year following birth [23]. Moreover, EEG non-linear characteristics can be exploited by statistical learning methods to classify ASD and non-ASD participants [8], [24].

Processing enormous datasets is now an issue of the development of deep learning models that are supported by artificial intelligence. In the field of deep learning, the most popular type of model is the convolutional neural network (CNN), which is also prevalent in a variety of medical specialities. A deep learning model is capable of carrying out both the extraction of features and the classification of data. In addition, the retrieved features have a high enough level of recall to pick up on very minor differences [25].

Deep learning surpasses traditional machine learning approaches as a result of its superior feature extraction [26]. CNN uses the features that it has gathered from its deep layered structure in order to do classification or regression, much like an algorithm that is used in machine learning [26]. CNN models like VGG Net, GoogLeNet, ResNet, Inceptionv3, DenseNet, and AlexNet are only some of the numerous pre-trained CNN models that have found broad applications in image classification and pattern recognition [27].

Pre-trained models are seeing more and more use, particularly as a result of transfer learning that has made it possible to create more successful models with a smaller set of training data by modifying the structure of a network that has been trained in the past [28].

Using CNN architectures, one can extract features from images [28]. from the fully connected layers, to extract features and classify them even further. Therefore, the use of the machine learning algorithm as opposed to the aforementioned layer can result in the accomplishment of successful classifications. Thus, using a variety of different machine learning algorithms illustrates various benefits that each of these algorithms offers [29].

It is of the utmost importance to locate the method of machine learning that provides the best results in relation to the particular application like Naive Bayes (NB), Support Vector Machine (SVM), k-Nearest Neighbour (KNN), and Decision Tree (DT) are the ones that are most commonly used and favoured in academic works [20], [30], [31].

The KNN algorithm is a clear and simple method that can be understood with little effort, it is an example of a supervised machine learning technology that has been used due to its ability to process multi-dimensional data, its high level of precision, and its adaptability [32]. The SVM, has gained a substantial amount of traction in the field of biomedical in recent years. source [33]. The DT algorithm is a type of supervised machine learning that is used for the categorization of big datasets by adopting a hierarchical tree-like structure made up of leaves, branches, and nodes [34].

In order to improve the diagnostic accuracy of ASD, machine learning and deep learning have been supplemented with EEG signals, however, classification systems for the autistic brain have research problems [9], [35].

As a result of recent research studies [8], [36], both the performance and accuracy of the EEG-based ASD recognition task have lately undergone substantial efforts. However, the vast majority of the works that are now available suffer from the same weaknesses in a few key areas. To begin, the vast majority of models have only been validated using a single dataset; as a result, such models have the potential to be data-dependent and may not be as robust as they may be. Second, the majority of the research that has been conducted for the EEG-based diagnosis of ASD has focused on developing models that are founded on the concept of machine learning. Several of the researchers have already started working on a solution to this problem by constructing specialised deep learning models. These models are currently in the process of being developed. However, because these models are extremely simplistic, they are unable to deal with the complexities of the situation, which leads to a low degree of classification accuracy. This issue is caused by the fact that these models are overly simplistic. An EEG-based ASD detection challenge served as the impetus for this research, which was motivated to give a deep hybrid multi-model-based deep learning for automatic ASD diagnosis using seven pre-trained CNNs deep learning models. The objective of this research was to address the problem. This strategy is proposed in this work with the intention of filling the gap that was discussed earlier. It is essential to emphasise the fact that this pre-trained CNNs deep learning models ASD EEG-based dataset has been utilised for the very first time in the specific area of research that is being investigated.

In this study, a 19-channel EEG time series is used to compute a spectrogram, which is then shown in three dimensions (3)-D spectrogram images). In order to accomplish the necessary multi-classification tasks and extract useful characteristics from these images, seven pre-trained CNNs including AlexNet [37], ResNet18 [38], GoogLeNet [39], MobileNetV2 [40], SqueezeNet [41], ShuffleNet [42] and EfficientNetb0 [43] in order to automatically identify mild, moderate, severe individuals with ASD and normal by analysing their EEG spectrogram images to get the benefits of transfer learning to classify scalograms. In addition, the DT, KNN, and SVM machine learning classification techniques were applied to the output features from the convolutional and pooling layers of the modified CNNs model in order to further classify the characteristics extracted by the deep CNNs in order to separate them into their respective categories.

The main contributions of the current study lie in the development of an EEG-based dataset that comprises individuals with mild, moderate, and severe types of ASD conditions, as well as normal controls. Indeed, EEG signals have, as far as we're aware, never been invested in any practical use. In addition, seven distinct state-of-the-art pre-trained deep CNN networks were used in conjunction with a machine learning classifier to autonomously diagnose ASD utilising deep and hybrid frameworks based on EEG characteristics derived from individuals with autism spectrum disorder. Highlighting the challenges of diagnosis and therapy while emphasising the need for effective therapeutic procedures. If cases of ASD could be diagnosed in the preclinical phase, while patients are still asymptomatic, it would allow for early and more effective treatment options and improved overall care.

A. RELATED WORK

Clinical procedures are employed with the purpose of detecting autism, mostly depending on behavioral data and, in severe instances, neuroimaging techniques. The utilization of machine learning in quantitative methodologies has been extensively researched and advanced as a means to address challenges associated with therapeutic techniques. The utilization of quantitative methods in this context is heavily reliant on machine learning techniques. Specifically, there are intricate approaches rooted in deep learning that have been devised to expedite the process of identifying and diagnosing ASD [44].

Machine learning is a subset of the field of Artificial Intelligence (AI), characterized by the ability of systems to acquire knowledge and improve performance via experience, rather than relying on explicit programming. Machine learning is employed to develop intricate models that can effectively classify or predict various sorts of data with a high level of accuracy. Deep learning, which falls under the category of machine learning, employs several layers of non-linear information processing to extract features, perform transformations, analyze patterns, and carry out classification tasks, either in a supervised or unsupervised manner [9].

Baygin et al. [45] presented two novel algorithms which are one-dimensional local binary patterns which are used as input of short-term Fourier transform to generate spectrogram image and hybrid deep lightweight feature generators. The proposed hybrid deep lightweight feature generator incorporates three lightweight deep network architectures for feature extraction. These are MobileNetV2, ShuffleNet, and SqueezeNet. The proposed model achieved 96.44% accuracy using a support vector machine (SVM) classifier. The results indicate that the proposed model is suitable for autism detection using EEG signals and can serve as an adjunct tool to aid neurologists during autism diagnosis in medical centres.

Hendr et al. [46] introduced the utilization of handwritten tasks as a means of studying people with the objective of early detection of ASD using computer-aided diagnosis. The dataset, consisting of both participants with ASD and those without ASD, underwent image processing techniques. Subsequently, the processed images were utilized to train a transfer learning network. The dataset was utilized in order to suggest a solution for automated ASD diagnosis using deep learning techniques. The GoogleNet transfer learning algorithm was employed to train and classify each handwritten task in the dataset. The results obtained from the proposed model demonstrate promise, as evidenced by an accuracy of 90.48%, recall of 80%, and specificity of 100%. These encouraging findings warrant further research and experimentation in this area. The findings of this study indicate that the utilization of handwritten task data yields superior performance and holds considerable significance in the identification of individuals with ASD [46].

Din and Jayanthy [47] used EEG data with pre-trained deep convolution neural networks to identify ASD. To train the pre-trained CNNs, GoogLeNet and SqueezeNet for identifying ASD individuals and normal controls using their EEG data, the study employed a transfer learning technique. The GoogLeNet and SqueezeNet algorithms successfully classified the scalograms produced from the EEG signals of ASD participants and healthy control subjects with 75% and 82% accuracy, respectively. The article comes to the conclusion that pre-trained deep convolution neural networks may accurately identify ASD from EEG readings.

Sridurga et al. [48] used two variants of CNN models, Xception and VGG19, to detect autism spectrum disorder. The requisite dataset was compiled from face images consisting of an equal number of healthy and autistic patients. The results demonstrated that the Xception model has an accuracy of 86% whereas the VGG19 model only provides an accuracy of 81%.The results indicated that the proposed system can be used in real-time applications to assist physicians with early patient diagnosis.

Ismail et al. [44] used facial images to predict whether the person is either autistic or a typically developing child. The Efficient Net convolutional neural network was utilized to build this model, which achieved an accuracy level of 88%.

Using temporal dynamic features of fMRI data, Al-Hiyali et al. [49] proposed a deep learning model for the diagnosis of ASD for 82 subjects (41 ASD and 41 normal cases) collected from three different sites of Autism Brain Imaging Data Exchange (ABIDE). The model employs pre-trained convolutional neural networks for feature extraction and two classifiers for classification using SVM and KNN. The KNN classifier with DenseNet201 as a pre-trained model produced the greatest results, with an accuracy of 85.9%, recall of 79.3%, and specificity of 92.2%. The proposed model can be used to analyze fMRI data related to brain disorders and is a useful diagnostic tool for ASD.

Alam et al. [50] have sought to identify the most effective transfer learning model for ASD classification. An empirical study has been conducted to adjust hyperparameters and optimizers for model training, taking into account five widely used and existing CNN-based models including VGG19, EfficientNetB0, Xception, MobileNetV2, and ResNet50V2. The study reveals that the modified Xception model demonstrates the highest performance, with 95% accuracy, AUC of 98%, a precision of 95%, and recall values of 95% compared to VGG19 which has an accuracy of 86.5%, ResNet50V2 has an accuracy of 94%, while MobileNetV2 and EfficientNetB0 have an accuracy of 92% and 85.76% respectively.

II. MATERIALS AND METHODS

A number of signal processing stages would be applied to the recorded EEG in order to distinguish the signals of ASD patients with varying degrees of severity from those of normal control subjects, allowing for a more accurate diagnosis of ASD signs automatically. Figure 1 is a block diagram of the proposed methodology.

For the current study investigation, the EEG signals were segmented into 5 sec and each was converted into a 2-D grey scale spectrogram image using the power spectral density *PSD* method. After that, the state-of-the-art pre-trained CNN models like AlexNet, SqueezNet, MobileNetV2, GoogleNet, ResNet18, ShuffleNet, and EfficientNet are utilised in order to extract features from each spectrogram image and classify them first then hybrid models are performed using DT, KNN and SVM classifiers to discriminate these features as normal subjects, mild, moderate, and severe ASD patients, respectively. The combination of seven different CNN models and three different machine learning approaches is analysed and contrasted in order to determine which combination produces the best successful outcomes from these methods. The results of the classification at the end of the study were evaluated using performance metrics.

A. EEG DATASET FOR ASD DETECTION

30 children were diagnosed with ASD, ranging in severity as mild, moderate and severe, and 10 children served as controls, all within the same age range. Ten normal subjects (5 females and 5 males; the age of 8.545Â±1.1 years), ten mild ASD patients (4 females and 6 males; the age of 8.182Â±1.025 years); ten moderate ASD patients (3 females and 7 males; the age of 8.364Â±0.8 years); ten severe ASD patients (3 females and 7 males; the age of 8.727Â±0.98 years; mean Â± standard deviation SD).

The patients were recruited for the study from the Autism Center in Pediatric Hospital, and the Neurophysiology department at Baghdad Teaching Hospital in Medical City, Baghdad, Iraq. Before the EEG recording, none of the children diagnosed with ASD had taken any kind of medicine for at least two weeks. The youngsters that comprised the control group had all attended regular, healthy schools and did not have a family history of neurological or mental conditions.

Each interview and diagnosis was carried out by a child and a psychiatrist in accordance with the criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) [51]. In addition, participants were screened the ASD severity using the Gilliam Autism Rating Scale (GARS-3) [52].

An EEG lasting ten minutes was obtained by utilizing an EEG machine (Nihon Kohden Company, Japan), 19 Ag/AgCl electrodes were placed (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, T5, T4, T6, P3, Pz, P4, C3, Cz, C4, O1, and O2) in accordance

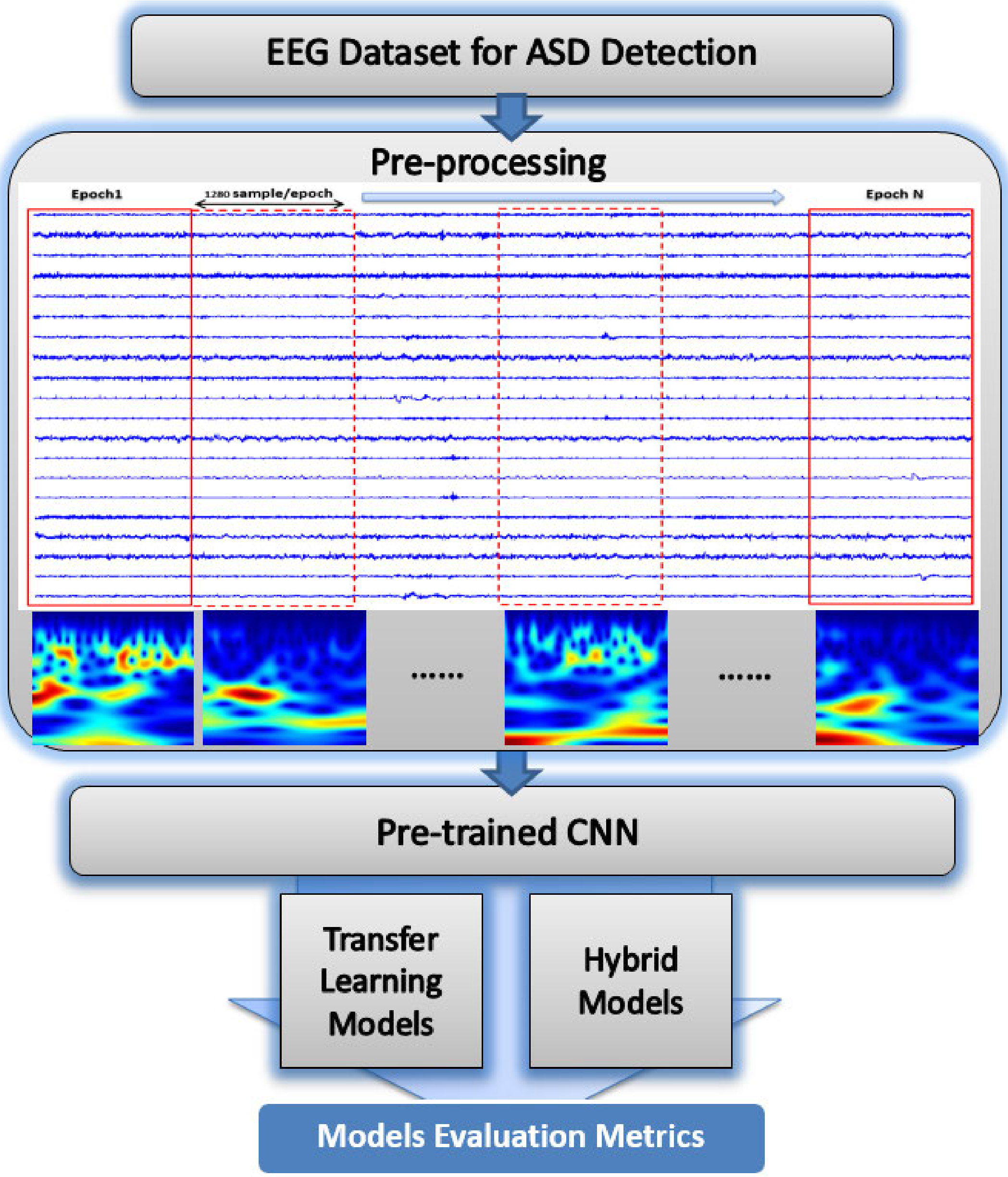

FIGURE 1. Schematic diagram of this study on ASD detection through EEG signals.

with the 10–20 system, in addition to two reference electrodes placed on both the mastoid. The information was gathered by the use of a sampling frequency of $fs = 500Hz$, a resolution of 12*bits*, and an impedance of less than $5K\omega$. During the recording process, the settings for the bandpass filter were (0.1–70 Hz), while the notch filter was at $50Hz$. Bandpass filtering was performed on the data in the range of $0.1 - 64Hz$ in preparation for analysis.

All of the procedures that were carried out as part of this research were done so in a manner that was compliant with the ethical standards established by the institutional research committee at the University of Baghdad/College of Medicine, as well as the 1964 Helsinki Declaration and any revisions that have been made to it since then. Before any of the children participated in the study, their parents provided their written consent after receiving appropriate information.

B. PRE-PROCESSING

In the first stage of processing each channel of recorded EEG datasets, the sampling frequency was set at $fs = 500Hz$; conventional filters, including a notch filter at $50Hz$, were used to get rid of interference noise; and a band pass filter with a $0.5 - 64$ Hz frequency range was used to limit the band of the recorded EEG signals [16].

After that, the EEGs were downsampled to a sampling frequency of $fs = 256Hz$ and segmented into non-overlapping epochs of 5 sec length. In the subsequent step, each of the 19 denoised EEG channels had its signal split into non-overlapping epochs of 5 sec length. Due to the fact that $fs = 256Hz$, each epoch contains $N = 1280\ samples$.

We were able to determine the value of the power spectral density PSD to be between 0.5 and 64 based on these epochs. The traditional method of estimating PSD is referred to as a periodogram, and it is obtained from the frequency distribution of the EEG signals [31]. The evaluation of the PSD can be used to describe the Fourier transform of the autocorrelation function. To be more specific, the following in Equation 1 describes the periodogram of a signal with a length of L [31].

$$PSD(f) = \frac{T_s}{L}\left|\sum_{l=0}^{L-1} x_l e^{-2\pi i f l}\right|^2 \tag{1}$$

where $-\frac{1}{2T_s} < f \leq \frac{1}{2T_s}$ and $\frac{1}{2T_s}$ is the sampling period. The following modified periodogram is obtained by multiplying the input time series by the window function w_l as in Equation 2:

$$\widehat{PSD}(f) = \frac{T_s}{L}\left|\sum_{l=0}^{L-1} w_l x_l e^{-2\pi i f l}\right|^2 \tag{2}$$

Spectral profiles have been widely used to characterise dementia phases using conventional classification methods and to extract empirically specified variables [25], [53]. Moreover, spectrogram images generated form time series are well suited for analysing biological signals due to its great resolution [54]. Therefore, in this research, the PSD of the xth EEG time series from individuals with mild, moderate, and severe ASD, as well as healthy controls were obtained using a modified periodogram with a rectangular windowing function to limit spectral leakage and smoothing out the edges of the signal, allowing for the generation of EEG spectrogram images.

A 2-dimensional grayscale spectrogram image was created by mapping the PSD images in question to an intensity value between 0 and 1 (where 0 (black pixel) and 1 (white pixel) correspond to the minimum and maximum of the $PSDs$, respectively). However, the EEG 2-D PSD are represented as images, thus they needed to be scaled into 3-D images to fit the individual state-of-the-art pre-trained CNN networks input architecture utilised for the automatic extraction and categorization of features in this study.

C. PRE-TRAINED CNN

The CNN is one of the well-known diagnostic methods that has had extensive application in the field of biomedical [45]. Convolutional layers, pooling layers, batch normalisation layers, fully connected (FC) layers, and finally a softmax layer are all part of the CNN networks [28].

Pooling the layers that learn feature maps with either the maximum or the average operator yields the most significant features as a result. At some point in time, the FC layers will supply the Softmax layer with resultant features for the layer to classify [55], [56]. In order to resolve non-linear issues, non-linear layers such as rectified linear unit (ReLU) functions were added to the network in order to make it more robust. After each convolutional and fully connected layer, the ReLU activation function is applied after the layer to which it is applied [57], [58].

In addition to that, the batch normalization and dropout approaches are addressed as potential solutions to the overfitting problem that exists within this neural network. CNN which has been pre-trained is a network that has been fine-tuned on extensive image content and has many different classes [57].

Seven individual state-of-the-art pre-trained deep CNN networks were trained on the ImageNet [59] database including AlexNet, ResNet18, GoogLeNet, MobileNetV2, SqueezeNet, ShuffleNet, and EfficientNetb0. For instance, AlexNet is a pre-trained deep CNN network which trained on set of images for a visual object detection project consisting of 1.2 million images from 1,000 different classes [37].

However, a network called AlexNet is a groundbreaking CNN architecture that has been popular since it won the ImageNet Large Scale Visual Recognition Challenge [59]. It is made of five convolutional blocks, then regular max-pooling layers and three fully connected networks. Using AlexNet, deep convolutional neural networks became more effective at classifying images. It pioneered the idea of ReLU Layer, max-pooling layers with overlapping regions and dropout regularizer [59]. Furthermore, ResNet18 is a version of the famous architecture named Resnet, which is short for a residual network known has its structure as being deep. ResNet18 has 18 layers, in addition to the convolutional ones which contain several batch normalizations and residual connections. In residual connections, the flow of information is directly from early layers to late layers thus solving vanishing gradient problem. ResNet18 is one of the simplest and symmetric clean network few nice accuracy also on this scenario [37]. In addition, GoogLeNet, was later introduced for feature extraction from different levels. GoogLeNet makes use of different sizes in parallel convolutional pathways and concatenates their results. It fosters both the breadth and depth of networks. At the same time, GoogLenet utilises spatial reduction using 1×1 convolutions to reduce feature map dimensions and make computations more efficient. It was engineered to be deeper and more efficient than the previous architects [37]. Immediately, MobileNetV2 is a CNN design for mobiles and embedded systems that have low computing power capabilities. It adopts depth-wise separable convolutions that break the original standard one into two dimensions, i.e., when convolving 7×9 kernels on a flowchart containing three hundred eighty elements and sixty units of width in height for each circuit level This reduces the number of parameters and computational costs without compromising accuracy, which is also good. MobileNetV2 has

TABLE 1. Specifications of the pre-trained deep network used in this study, Network Size in (MB) and No. of parameters in (Millions).

CNN Networks	Network depth	Network size	No. of parameters	No. of layers	Features layer name
AlexNet	8	227	61	25	'drop7'
ResNet18	50	44	11.7	71	'pool5'
GoogLeNet	22	27	7	144	'pool5-drop$_7x7_s1'$
MobileNetV2	53	13	3.5	154	global_average_pooling2d$'_1$
SqueezeNet	18	5.2	1.24	172	'conv10'
ShuffleNet	50	5.4	1.4	172	'node$_2 00'$
EfficientNetb0	82	20	5.3	290	efficientnet-b0|model|head| global$_a verage_p ooling2d$| GlobAvgPool'

inverted residual blocks with linear bottlenecks that facilitate the capture of a more complex object without sacrificing efficiency [37]. Moreover, SqueezeNet is a lightweight CNN architecture capable of producing high accuracy without losing efficiency. It does this by employing the use of squeeze layers that uses one-by-one convolutions to reduce input channels which are then followed by expanded layers using larger convolution kernels. In certain layers, SqueezeNet also transforms 3×3 filters into regular universal filters to minimize computational complexity. SqueezeNet has a network structure that enables it to obtain better performance in terms of accuracy level when compared with larger models, at approximately lower levels of parameters [37]. ShuffleNet is also a model aimed at reducing the cost of computation for CNN models while still preserving accuracy. It defines channel shuffling, which allows transferring and exchanging information across various groups of channels. ShuffleNet uses point group convolutions and channel shuffling which not only considerably reduces the number of parameters but also computational complexity. Shuffling the channels enables the network to capture local and global dependencies efficiently [37]. Ultimately, the EfficientNet is a sequence of CNN architectures that achieve top performance with low run time. This series of the model consists of a baseline type, which is called EfficientNet B0. It applies compound scale which uniformly scales the depth, width and resolution of network. The architecture is essentially a stack of blocks constructed in the same pattern but with varying layer counts, squeeze-and-excitation passes and mobile inverted bottleneck layers. With an accuracy-efficiency balance, unsurprisingly EfficientNet B0 is a basis reference for other members of the family [37].

The CNN architecture of the seven individual state-of-the-art pre-trained deep networks were modified and were employed for this three-way classification task and the dataset is split 80% for training and validation and 20% for testing (80% : 20%) of the different epoch lengths and EEG-derived images. The specifications of the pre-trained deep network used in this study are shown in Table 1.

In this study, the spectrogram 3-D images were employed for the purpose of classifying individuals with ASD and control people. The neural networks AlexNet, ResNet18, GoogLeNet, MobileNetV2, SqueezeNet, ShuffleNet and EfficientNetb0, all of which had been pre-trained, were utilised. These networks had previously been pre-trained to categorise photos into one thousand different categories, and we have since retrained the network. Every one of those layers served as a filter in turn. The earliest levels extract the more general characteristics of the images, whereas the latter layers extract the more particular features. The features are extracted by the convolution layers, and the final classification layer is the one that is utilised for classification. In order to prevent over-fitting, a dropout layer was utilised. Through this training, we hope to improve our accuracy and reduce the amount of loss function that occurs. The recommended input size for images for GoogleNetV2, ResNet, VGG19, ShuffleNet, and EfficientNetb0 is $224 \times 224 \times 3$. When compared to this, the input size for other neural networks such as AlexNet and SqueezeNet was $227 \times 227 \times 3$.

1) TRANSFER LEARNING MODELS

The transfer learning phase involved using a big dataset to generate insights and then applying those insights to a smaller target dataset. Pre-trained models that were also trained on the ImageNet dataset are a prominent resource for transfer learning. The images in the ImageNet dataset have been divided into over a thousand different categories, including everything from natural objects and humans to plants and animals. Multiple applications have made extensive use of pre-trained models drawn from the ImageNet dataset to deal with the problem of scarce data [60]. The value of transfer learning using pre-trained models increases when the target task dataset has similar properties to ImageNet. The ImageNet dataset may not immediately improve the usefulness of 19-channel EEG time series signals because it mostly comprises 3-D images, but this should not be overlooked. This difference between 3-D and EEG signals emphasises the necessity for careful thought and customization when applying transfer learning approaches to problems involving EEG datasets, many of which require specific preprocessing to overcome the EEG time series representations issue [47], [54].

In the present study, Transfer Learning was utilised with pre-trained CNNs in order to complete the three-way classification work consisting of mild, moderate, and severe ASD patients, as well as normal control subjects. In the first part of the process, various neural networks, such as AlexNet, ResNet18, GoogLeNet, MobileNetV2, SqueezeNet, ShuffleNet and EfficientNetb0, were utilised to train on the spectrogram images of ASD patients and normal subjects. After that, loading all of the pre-trained models to replace the classification output layout, needs to be done so that the weights of the final entirely linked layer can be reduced from the typical one thousand classes to four classes. The last three layers, including the fully connected layer, the softmax layer, and the classification output layer, were eliminated and replaced by three new layers. These three new layers are the fully connected layer-New, the softmax layer-New, and the classification layer-New. This was done in order to meet the number of class requirements that were necessary in order to discriminate mild, moderate, and severe ASD as well as normal control subjects.

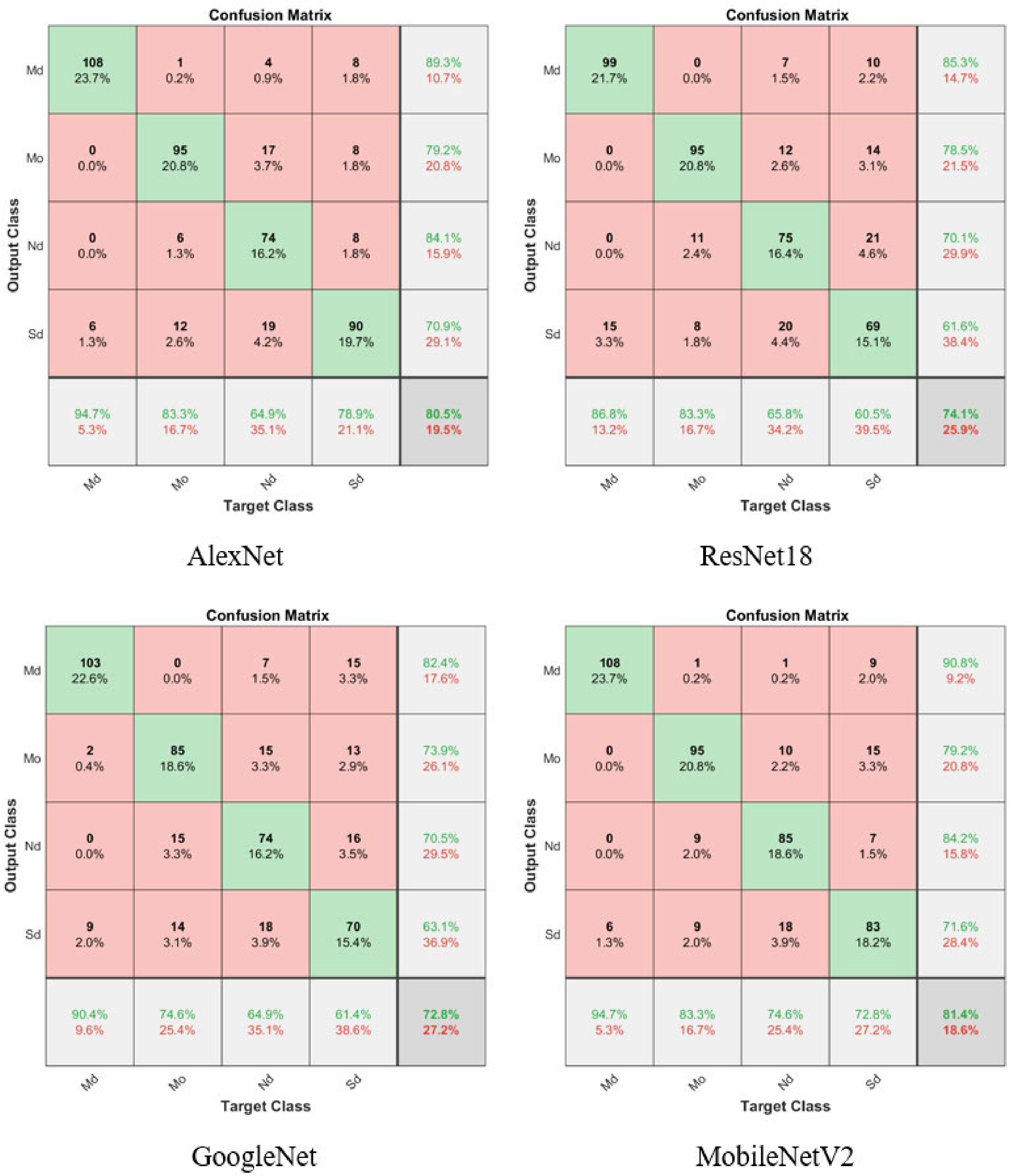

FIGURE 2. The confusion matrices of the AlexNet, ResNet18, GoogleNet and MobileNetV2 pre-trained transfer learning networks for classifying mild, moderate, severe and normal subjects.

2) HYBRID MODELS

Applying the pre-trained CNN models requires a computer with high specification and intensive computation capability, as it takes a long time to train the model using the 3-D spectrogram images modified from the EEG dataset. Therefore, the hybrid method will address these challenges. This section describes how the hybrid method combines CNN models with the DT, KNN and SVM classifiers.

EEG-based ASD severity detection utilising hybrid learning has been further investigated. Machine learning classifiers DT, KNN and SVM are integrated into each of the seven state-of-the-art pre-trained deep CNN networks to classify the 3-D

FIGURE 3. **The confusion matrices of the SqueezNet, ShuffleNet and EfficientNet pre-trained transfer learning networks for classifying mild, moderate, severe and normal subjects.**

spectrogram images into mild, moderate, severe, and normal categories involving using the feature map matrices of seven state-of-the-art pre-trained deep CNN networks [45].

Feature matrices were extracted individually, transformed into a vector by the global average pooling layer, fed into a fully connected layer, and then illustrated by the Softmax and Classifier Output layers [61], [62]. Completely connected layers allowed us to incorporate features from multiple networks into a single model. Standard metrics for evaluating classification systems and a confusion matrix were used to determine the effectiveness of the suggested approach. To create deep feature maps for use in DT, KNN and SVM

FIGURE 4. **Confusion matrices utilising pre-trained AlexNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.**

models for machine learning, the "global average pooling layer" is employed.

- Deep Features Extraction: As the ImageNet has Large Scale Visual Recognition Challenge [37] which was won by AlexNet, a revolutionary CNN [37], the AlexNet uses a sequence of five convolutional layers to decrease the picture size from 224 × 224 to 13 × 13 and the filter response depth from 96 to 256 using max pooling and rectified linear unit (ReLU) [37].

In this study, we applied transfer learning to networks of CNNs to classify conditions into mild, moderate, severe, and normal categories. 3-D images from the epoch lengths of 5 sec were resized into 227 × 227 × 3 before being input into the AlexNet and SqueezeNet

FIGURE 5. Confusion matrices utilising pre-trained ResNet18 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.

models and resized to the dimensions of 224 × 224 × 3 before being fed into GoogleNetV2, ResNet, VGG19, ShuffleNet, and EfficientNetb0 models. Since there are four classes, we replaced CNN's final fully linked layer with a new final classification layer consisting of four nodes.

- Machine Learning Classifiers: Thanks to CNN's automatic feature learning capabilities, ASD categorization using deep neural networks is becoming more and more common [8]. Based on the outcomes of the classification, current works can be separated into four categories from different perspectives.

FIGURE 6. **Confusion matrices utilising pre-trained GoogleNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.**

3-D images are fed into the seven individual pre-trained CNN models to extract the deep features of these images. Another strategy for classifying pre-processed 3-D ASD and normal images involves pooling the feature map matrices from many CNN deep networks and feeding them into a fully connected layer, as shown by the Softmax and Classifier Output layers. Deep feature maps were created using the features layer of each CNN 1 and the last layers of the CNN models were removed and replaced with the DT, KNN and SVM classifiers, respectively.

D. MODELS EVALUATION METRICS

In this research, the classification accuracies were calculated by using seven individual state-of-the-art pre-trained deep CNN networks firstly, and DT, KNN and SVM machine

FIGURE 7. **Confusion matrices utilising pre-trained MobileNetV2 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.**

learning classification models secondly to classify the EEG dataset into two classes are children with ASD into mild, moderate, severe and normal control children. To prevent class imbalance, the dataset is split 80% for training and validation and 20% for testing (80% : 20%).

The scope of the evaluation is broadened by including segment-based and event-based performance outcomes. Estimating seizure prediction performance requires defining the true positive rate (TP) as the number of EEG segments that were correctly identified as preictal, the true negative rate (TN) as the number of EEG segments that were correctly classified as interictal, the false positive rate (FP) as the number of EEG segments that were incorrectly classified as preictal, and the false negative rate (FN) as the number of

TABLE 2. Transfer learning results of evaluation metrics for classifying mild, moderate, severe patients and control people using all 7 pre-trained networks.

Network	Metrics	Mild	Moderate	Normal	Severe	Average
AlexNet	precision	94.7	83.3	64.9	78.9	80.5
	recall	89.3	79.2	84.1	70.9	80.8
	specificity	98.2	94.3	89.1	92.7	93.6
	accuracy	80.5	80.5	80.5	80.5	80.5
	F-measure	91.9	81.2	73.3	74.7	80.3
ResNet18	precision	86.8	83.3	65.8	60.5	74.1
	recall	85.3	78.5	70.1	61.6	73.9
	specificity	95.6	94.3	88.8	86.9	91.4
	accuracy	74.1	74.1	74.1	74.1	74.1
	F-measure	86.1	80.9	67.9	61.1	74
GoogleNet	precision	90.4	74.6	64.9	61.4	72.8
	recall	82.4	73.9	70.5	63.1	72.5
	specificity	96.7	91.5	88.6	87.2	91
	accuracy	72.8	72.8	72.8	72.8	72.8
	F-measure	86.2	74.2	67.6	62.2	72.6
MobileNetV2	precision	94.7	83.3	74.6	72.8	81.4
	recall	90.8	79.2	84.2	71.6	81.4
	specificity	98.2	94.3	91.8	90.9	93.8
	accuracy	81.4	81.4	81.4	81.4	81.4
	F-measure	92.7	81.2	79.1	72.2	81.3
SqueezNet	precision	95.6	89.5	80.7	76.3	85.5
	recall	93.2	83.6	82.9	82.1	85.4
	specificity	98.5	96.4	93.6	92.3	95.2
	accuracy	85.5	85.5	85.5	85.5	85.5
	F-measure	94.4	86.4	81.8	79.1	85.4
ShuffleNet	precision	86	70.2	64	55.3	68.9
	recall	80.3	69	63.5	61.2	68.5
	specificity	95.2	90	88	85.6	89.7
	accuracy	68.9	68.9	68.9	68.9	68.9
	F-measure	83.1	69.6	63.8	58.1	68.6
EfficientNetb0	precision	86	78.9	43.9	33.3	60.5
	recall	69.5	63.4	50	52.1	58.7
	specificity	94.9	92.4	82	80.2	87.4
	accuracy	60.5	60.5	60.5	60.5	60.5
	F-measure	76.9	70.3	46.7	40.6	58.6

EEG segments that were incorrectly classified as interictal. Equations 3 to 7 were used for calculating accuracy, recall, specificity, precision and F1-score.

$$Accuracy = (Tp + TN)/(TP + TN + FN + FP) \tag{3}$$

$$Recall = TP/(TP + FN) \tag{4}$$

$$Specificity = TN/(TN + FP) \tag{5}$$

$$Precision = Tp/(Tp + FP) \tag{6}$$

$$F1 - score = 2 \times (precision \times recall)/(precision + recall) \tag{7}$$

III. RESULTS AND DISCUSSION

A. RESULTS OF PRE-PROCESSING

A 10-minute (153600-sample) EEG recording was segmented into 120 non-overlapping epochs of 5 sec in length, with dimensions of $120 epochs \times 19$ *channels*. The data set was then analysed for mild, moderate, severe, and normal activity. In order to more accurately depict the corresponding spectral profiles, the segmented images were transformed into 2-D grayscale images.

Then, 2-D grayscale images were converted into 3-D images and resized to have the dimensions of $227 \times 227 \times 3$ before being input into the AlexNet and SqueezeNet models. On the other hand, the 3-D images were resized into $224 \times 224 \times 3$ to meet the specification of the input layer of GoogleNetV2, ResNet, VGG19, ShuffleNet, and EfficientNetb0 models.

TABLE 3. Results of evaluation metrics utilising pre-trained AlexNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	83.7	75.2	71.2	62.2	73.1
	recall	85.7	71.9	71.6	63.2	73.1
	specificity	94.4	92.1	90.4	87.2	91
	accuracy	73.1	73.1	73.1	73.1	73.1
	F-measure	84.7	73.5	71.4	62.7	73.1
KNN	precision	82.7	76.9	70	64.5	73.5
	recall	92.1	74.9	59.9	68.1	73.8
	specificity	93.6	92.5	91.4	87.5	91.3
	accuracy	73.8	73.8	73.8	73.8	73.8
	F-measure	87.1	75.9	64.6	66.3	73.5
SVM	precision	92.5	86	79.8	77.7	84
	recall	93.6	80.7	83	78.4	83.9
	specificity	97.5	95.6	93	92.5	94.6
	accuracy	83.9	83.9	83.9	83.9	83.9
	F-measure	93	83.3	81.4	78	83.9

TABLE 4. Results of evaluation metrics utilising pre-trained ResNet18 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	86.8	72.4	67.5	62.2	72.2
	recall	88.3	75.1	60.2	65.5	72.3
	specificity	95.5	90.4	90.4	86.7	90.8
	accuracy	72.3	72.3	72.3	72.3	72.3
	F-measure	87.5	73.7	63.7	63.8	72.2
KNN	precision	77.8	63.9	73.8	66.1	70.4
	recall	88	87.4	50.3	54.1	70
	specificity	91.6	83.5	94.1	90.7	90
	accuracy	70	70	70	70	70
	F-measure	82.6	73.8	59.8	59.5	68.9
SVM	precision	82.9	73.2	64.6	61.2	70.5
	recall	87.7	74.3	59.4	61.7	70.8
	specificity	94	90.9	89.2	86.9	90.3
	accuracy	70.8	70.8	70.8	70.8	70.8
	F-measure	85.2	73.7	61.9	61.4	70.6

B. RESULTS OF PRE-TRAINED CNN

The deep learning adaptive moment estimation *ADAM* optimizer with a mini-batch size of 64, a piecewise learn rate schedule with an initial learn rate of 0.00001, and a validation frequency of 3 were used.

The results of the study of the 3-class ASD and normal datasets with the proposed deep feature extraction and machine learning classification workflow will be shown in the following subsections.

1) RESULTS OF TRANSFER LEARNING MODELS

Tables 2 contain the results of the classification corresponding evaluation metrics that were obtained using seven state-of-the-art transfer learning CNN deep neural networks. In addition, the confusion matrix for each scheme is displayed in Figures 2 it has come to our attention that the classification accuracy as a whole is satisfactory for all three-way group classification tasks.

Confusion matrices Figures 2 and 3 demonstrate that employing transfer learning with a SqueezeNet model yields the highest classification accuracy, reaching 85.53%.

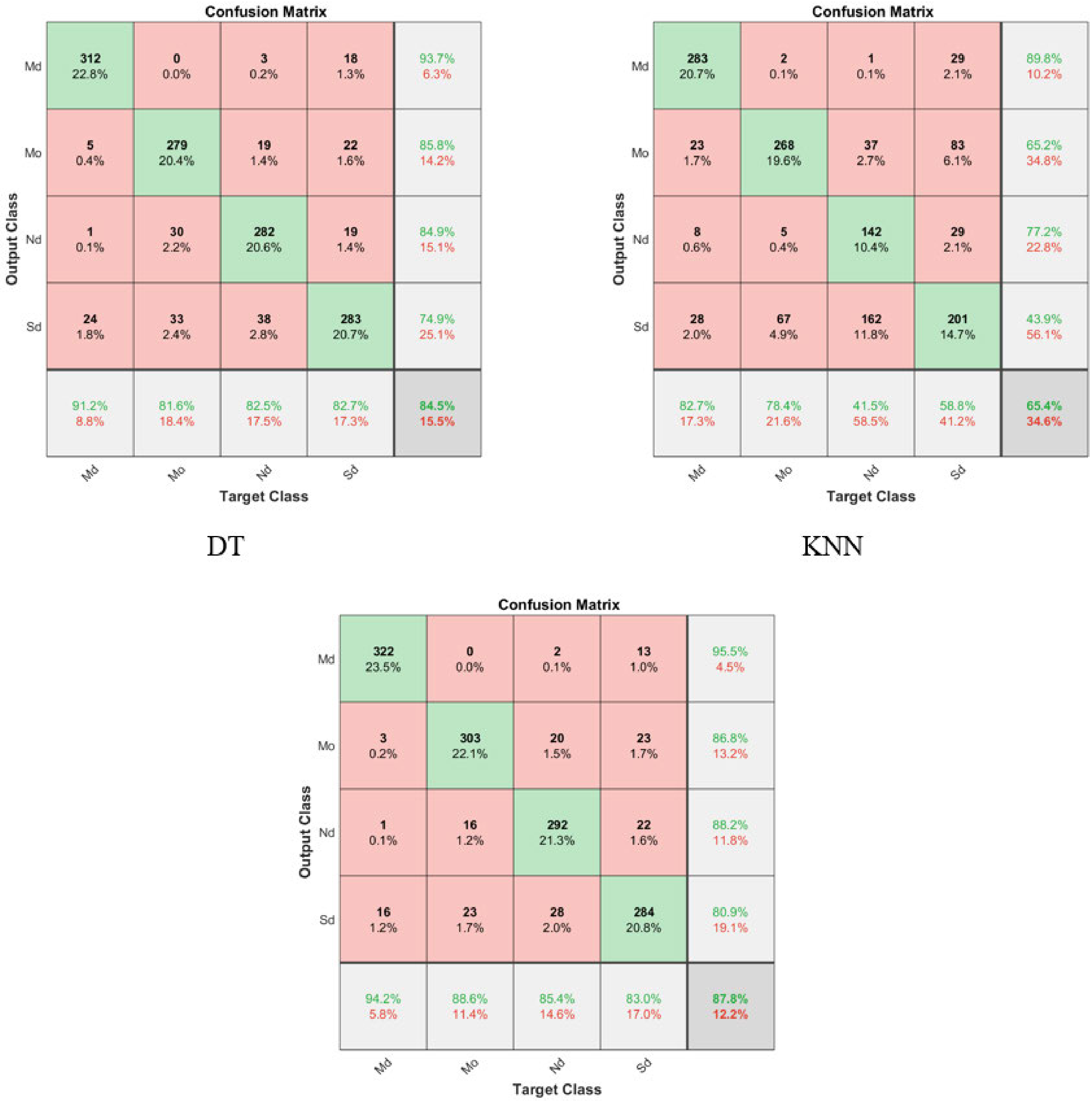

FIGURE 8. Confusion matrices utilising pre-trained SqueezeNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.

The subsequent models in the sequence are MobileNetV2, AlexNet, ResNet18, GoogLeNet, ShuffleNet, and EfficientNetb0, achieving accuracies of 81.4%, 80.5%, 74.1%, 72.8%, 68.9%, and 60.5%, respectively.

2) RESULTS OF HYBRID MODELS

Figures 4 show the confusion matrices for each scheme after using AlexNet with DT, KNN, and SVM classifiers, respectively to discriminate the mild, moderate, and severe patients and normal subjects. The classification results illustrate that the best result was achieved by using AlexNet with SVM classifier with an accuracy of 83.9%, as indicated in Table 3.

ResNet18 was used with DT, KNN, and SVM classifiers to differentiate between mild, moderate, and severe patients and normal people, and the resulting confusion matrices are displayed in Figures 5. According to Table 4, the results of the classification show that the best result was reached

FIGURE 9. **Confusion matrices utilising pre-trained ShuffleNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.**

by utilising ResNet18 with DT classifier at an accuracy of 72.3%.

The confusion matrices for each scheme are displayed in Figure 6 after GoogleNet was used with DT, KNN, and SVM classifiers to distinguish between mild, moderate, and severe patients and normal participants. Table 5 shows that the best classification result was obtained using GoogleNet with SVM classifier with an accuracy of 74.9%.

Confusion matrices for each method used to differentiate between mild, moderate, and severe patients and normal people are displayed in Figures 7 after MobileNetV2 was trained using DT, KNN, and SVM classifiers, in that order. According to Table 6, the best classification result was

TABLE 5. Results of evaluation metrics utilising pre-trained GoogleNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	81.3	65.9	57.6	58.8	65.9
	recall	82.7	66.1	58.8	56.4	66
	specificity	93.7	88.6	85.6	86.8	88.7
	accuracy	66	66	66	66	66
	F-measure	82	66	58.2	57.6	66
KNN	precision	84.5	66.3	65.4	55.9	68
	recall	84.8	76	44.7	65.2	67.7
	specificity	94.8	87.1	92.1	82.8	89.2
	accuracy	67.7	67.7	67.7	67.7	67.7
	F-measure	84.7	70.8	53.1	60.2	67.2
SVM	precision	87.4	73.8	71.3	67.2	74.9
	recall	87.1	73.4	68.1	70.8	74.9
	specificity	95.8	91.3	90.8	88.5	91.6
	accuracy	74.9	74.9	74.9	74.9	74.9
	F-measure	87.3	73.6	69.7	68.9	74.9

TABLE 6. Results of evaluation metrics utilising pre-trained MobileNetV2 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	70.7	69.1	59.2	49.3	62.1
	recall	77.8	65.5	55.6	50	62.2
	specificity	89.3	90.3	87.2	82.8	87.4
	accuracy	62.2	62.2	62.2	62.2	62.2
	F-measure	74.1	67.3	57.3	49.6	62.1
KNN	precision	74.9	75.1	76.9	71.4	74.6
	recall	96.2	84.5	67.3	51.2	74.8
	specificity	89.3	90.6	93.3	93.2	91.6
	accuracy	74.8	74.8	74.8	74.8	74.8
	F-measure	84.3	79.5	71.8	59.6	73.8
SVM	precision	88.1	83.6	81.7	70.1	80.9
	recall	91.2	80.7	77.2	74	80.8
	specificity	95.9	94.7	94.2	89.5	93.6
	accuracy	80.8	80.8	80.8	80.8	80.8
	F-measure	89.7	82.1	79.4	72	80.8

TABLE 7. Results of evaluation metrics utilising pre-trained SqueezeNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	93.7	85.8	84.9	74.9	84.8
	recall	91.2	81.6	82.5	82.7	84.5
	specificity	98	95.5	95.1	90.7	94.8
	accuracy	84.5	84.5	84.5	84.5	84.5
	F-measure	92.4	83.7	83.7	78.6	84.6
KNN	precision	89.8	65.2	77.2	43.9	69
	recall	82.7	78.4	41.5	58.8	65.4
	specificity	96.9	86.1	95.9	75	88.5
	accuracy	65.4	65.4	65.4	65.4	65.4
	F-measure	86.1	71.2	54	50.3	65.4
SVM	precision	95.5	86.8	88.2	80.9	87.9
	recall	94.2	88.6	85.4	83	87.8
	specificity	98.5	95.5	96.2	93.5	95.9
	accuracy	87.8	87.8	87.8	87.8	87.8
	F-measure	94.8	87.7	86.8	82	87.8

accomplished by combining MobileNetV2 and the SVM classifier, yielding an accuracy of 80.8%.

SqueezNet was used with DT, KNN, and SVM classifiers to differentiate between mild, moderate, and severe patients and normal people, and the resulting confusion matrices are depicted in Figure 8. Classification findings show that the best result was reached by combining SqueezNet with SVM classifier with an accuracy of 87.8%, as shown in Table 7.

TABLE 8. Results of evaluation metrics utilising pre-trained ShuffleNet with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	83.2	74.3	63.9	59.3	70.2
	recall	83.9	71.9	59.1	65.2	70
	specificity	94.3	91.7	88.9	85.1	90
	accuracy	70	70	70	70	70
	F-measure	83.6	73.1	61.4	62.1	70
KNN	precision	73.2	60.7	68	57.7	64.9
	recall	87.1	81.3	40.4	50.6	64.8
	specificity	89.4	82.5	93.7	87.6	88.3
	accuracy	64.8	64.8	64.8	64.8	64.8
	F-measure	79.6	69.5	50.6	53.9	63.4
SVM	precision	83.2	69.9	59.7	58.3	67.8
	recall	84.2	71.3	57.6	58.5	67.9
	specificity	94.3	89.8	87	86.1	89.3
	accuracy	67.9	67.9	67.9	67.9	67.9
	F-measure	83.7	70.6	58.6	58.4	67.8

TABLE 9. Results of evaluation metrics utilising pre-trained EfficientNetb0 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, as well as control people.

Classifiers	Metrics	Mild	Moderate	Normal	Severe	Average
DT	precision	67.6	56.4	48.2	45.2	54.3
	recall	70.2	57.9	46.2	44.2	54.6
	specificity	88.8	85.1	83.4	82.2	84.9
	accuracy	54.6	54.6	54.6	54.6	54.6
	F-measure	68.9	57.1	47.2	44.7	54.5
KNN	precision	65.8	64.2	59.1	51.7	60.2
	recall	86.3	68.7	43.9	45.3	61
	specificity	85.1	87.2	89.9	85.9	87
	accuracy	61	61	61	61	61
	F-measure	74.7	66.4	50.3	48.3	59.9
SVM	precision	81.3	70.4	63.6	59.2	68.6
	recall	86.5	69.6	58.2	61.1	68.9
	specificity	93.4	90.3	88.9	86	89.6
	accuracy	68.9	68.9	68.9	68.9	68.9
	F-measure	83.9	70	60.8	60.1	68.7

The confusion matrices for each scheme are displayed in Figure 9 after ShuffleNet was used with DT, KNN, and SVM classifiers to distinguish between mild, moderate, and severe patients and normal participants. Table 8 shows that the best classification result was obtained using ShuffleNet with SVM classifier with an accuracy of 67.9%.

The confusion matrices for each scheme are displayed in Figure 10 after EfficientNet was used with DT, KNN, and SVM classifiers to distinguish between mild, moderate, and severe patients and normal participants. Table 9 shows that the best classification result was obtained using EfficientNet with SVM classifier with an accuracy of 68.9%.

Results show that using hybrid models with a SqueezeNet gives the highest classification using SVM accuracy of 87.8%. followed by AlexNet, MobileNetV2, GoogLeNet, ResNet18, EfficientNetbo and ShuffleNet, respectively with accuracy of 83.9%, 80.8%, 74.9%, 70.8%, 68.9% and 67.9%, respectively.

One classifier performs better than the other because algorithm differences are tied to a variation in underlying algorithms that explain abifromces another has unique characteristics changes its performance. In addition, performance of different classifiers benefited from the use of deep neural networks in feature selection depends on how powerful these classifiers become capable as a result to efficiently utilize selected features. Mark the trend which refers to

FIGURE 10. **Confusion matrices utilising pre-trained EfficientNetb0 with DT, KNN, and SVM classifiers for mild, moderate, and severe patients, together with normal subjects.**

generalization performance, model complexity and generalization ability – highlighting that we are considering classifiers to make trade-offs between overfitting vs. underfitting.

IV. CONCLUSION

Deep CNNs such as AlexNet, ResNet18, GoogLeNet, MobileNetV2, SqueezeNet, ShuffleNet, and EfficientNetb0 were utilised in this study to classify EEG recordings made by patients with mild, moderate, and severe forms of autism as well as recordings made by healthy control subjects. This research tackled the difficult problem of classifying EEG recordings. Deep learning is able to overcome the restrictions that are associated with traditional learning algorithms, and it enables users to avoid the process of manually crafting and extracting features. The 3-D spectrogram of the EEG recordings has been analysed to look for abnormalities in the spectrum of people who have ASD. As a result, the development of an automated method that is predicated on the spectrum representation of EEG data was one of the most important contributions made by this study. To be more specific, we suggested a PSD-based CNN that is able to extract latent features from 3-D representations of EEG spectra and, as a result, distinguish between mild, moderate, severe, and normal patients using just non-invasive scalp EEG recordings. Extracting information through feature engineering about these physiological changes can assist specialists in increasing the quality of their analysis while also reducing the amount of time it takes to complete the analysis [63]. Current research has evolved beyond the feature engineering stage and is now focusing on comprehension and the extraction of knowledge using deep learning. This is being done so that the analysis process can be optimised even further. On the other hand, the prior research either used face recognition as Akhtar et al. used transfer learning-based autism face recognition framework to more precisely identify children with ASD in the early stages, which demonstrated the highest accuracy 92.10% in detecting autistic children more explicitly in the early stages [64], or in spite of using EEG, researchers did not take into account all of the EEG channels [45]. As a consequence, it is possible that some characteristics that may be relevant for ASD have been neglected, and the accuracy rate for automatic diagnosis is low. The ability to accurately classify data is possessed by deep models. As a result, deep models have been applied in this investigation to resolve classification issues based on the extraction of EEG spectrogram images. The results of this deep classification have achieved a high level of performance. EEG-based autism signals have never been used to be identified by a data-driven from seven individual state-of-the-art pre-trained deep CNN networks employing EEG spectrogram images, as far as we are aware. This is the best information we have regarding this topic. Mohi et al. [8] introduced pre-trained ASD and normal controls utilising the GoogLeNet and SqueezeNet with accuracies of 75% and 82%, respectively.

Directions for further work include creating an EEG-based drowsiness detection system that uses real-time data graphs to attain the needed simulation. Naturally in this case, we tap into our minds through brain-computer interfaces (BCI) insert that complement by examining the potential of individual fit versions to identify sleepiness using EEG data. There is a possibility that more advanced and personalized algorithms for the detection of lethargy can be developed by considering brainwave patterns associated with each person, along with personality-defining factors such as gender, age and strength on autism severity. Such regions may represent targets of future studies, which seek to boost the diagnostic possibilities for sleepiness in autism spectrum disorder patients.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

ETHICAL APPROVAL

All methods performed in studies involving human subjects were in compliance with the ethical requirements of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later revisions or comparable ethical standards.

DATA AVAILABILITY

The dataset utilised in this study is made available upon request.

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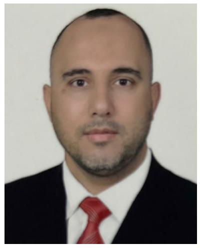

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