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Detection of Disruptive EEG Network and Scaling Severity for Epileptic Seizure

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Abstract - *Understanding the cortical connection of the brain requires the neurosurgeon to recognize epileptic seizure types. Despite the existence of automated early identification of seizures from a normal electroencephalogram (EEG), no attempts have been made to classify seizure types. As a result, using the Children's Hospital Boston EEG corpus, this study aims to categorize five variations of seizures with non-seizure EEG using convolutional neural networks (CNN) and transfer learning. Our aim is to do a multi-class classification of epileptic seizure types, which comprise simple partial, complicated partial, focal non-specific, generalized non-specific, and tonic–clonic seizures. Before feeding the 19-channel EEG time series to CNN, it was converted into a time-series-frequency stack. Using CNN, two distinct modalities were proposed: Transfer learning with a pre-trained network and extracting visual features with a pre-trained network, classifying with a Random Forest classifier. The results revealed that a CNN-based strategy outperformed feature and clustering-based approaches. It may be inferred that EEG-based seizure type categorization using the CNN model might be helpful in pre-surgical evaluations for epilepsy patients.*

Key Words **:** Convolutional Neural Network, Classification, Electroencephalography, Epileptic Seizure, Random Forest

1.INTRODUCTION

A change in the electrical activity of the brain causes epileptic seizures, which can be classified as focal, generalized, or undetermined. The correct categorization of epileptic seizure types is critical for epilepsy patient's therapy and illness management [1]. Focal seizures begin on one side of the brain and are characterized as simple partial or complex partial seizures based on the patient's level of consciousness during the seizure. Absence, tonic, atonic, clonic, and tonic–clonic, myoclonic seizures are all types of generalized seizures that affect both sides of the brain at the same time. Motor and non-motor symptoms that include movement are used to classify generalized seizures [2]. Jerking motions, stiff or rigid muscles, weak or limp muscles, and short muscular twitching are all examples of motor signs. Unknown seizures occur when the commencement and location of the seizure are unknown [3].

The kind of epileptic seizure has an impact on medicine selection and patient safety. The majority of the research in the literature focuses on using machine learning to identify seizures automatically. The use of machine learning and deep learning, particularly convolutional neural networks, for multi-class seizure type classification is in high demand. Manual examination of long-term electroencephalogram recordings, which might span many days or weeks, is a time-consuming process, as we all know [4]. The development of an automated method for the categorization of multi-class seizure types requires special consideration. As a result, we identified seizure types using EEG alone in this research, rather than motor symptoms, degree of consciousness, or video EEG. Automated processes like this might aid the neurological community in making better clinical decisions and determining the best treatment for epilepsy patients.

2. LITERATURE SURVEY

In recent investigations, CNN has been used to categorize epileptic episodes. Using the University of Bonn database, a 13-layer deep CNN exhibited an accuracy of 88.67 percent in a recent research. The true positive rate between seizure and non-seizure EEG activity was 74.0 percent in a plot EEG image-based investigation employing CNN. Using the Freiburg Hospital intracranial EEG dataset, the Boston Children's Hospital-MIT scalp EEG dataset, and the American Epilepsy Society seizure prediction challenge dataset, seizure prediction with intracranial and scalp electroencephalogram signals had a sensitivity of 81.4 percent, 81.2 percent, and 75.0 percent, respectively [5].

Neonatal seizure detection utilising deep CNN with 26 newborns yielded a 77.0 percent seizure detection rate. When discriminating between focal and non-focal signals, signal transforms utilising empirical mode decomposition and classification using CNN had an accuracy of 98.9%. In the same study, 99.5 percent of non-seizure vs. seizure recordings were correctly classified, 96.5 percent correctly classified healthy, non-focal, and seizure recordings, and 95.7 percent correctly classified healthy, focal, and seizure recordings [5]. Using the Freiburg and CHB-MIT datasets, a CNN-based model had the maximum accuracy of 96.7 percent and 97.5 percent, respectively [6].

Another study proposes employing pyramidal 1-dimensional CNN for binary classification of seizure vs. non-seizure and normal vs. ictal using the University of Bonn database. Similarly, deep neural networks were used to achieve an F-measure of 95.0 percent between seizure and non-seizure classification. The area under the curve for real-time seizure identification was 78.33 percent when dynamic EEG records were categorized using CNN [7]. Without utilising non-seizure EEG data, a recent study employing machine learning for 7-class seizure type categorization produced an F1 score of 0.907. Deep CNN architecture was used on the TUH database to produce a sensitivity of 30.83 percent and a specificity of 96.86 percent [8].

The robust features acquired from images-based representations of EEG spectrograms in three frequency bands (0–7, 7–14, and 14–49 Hz) were used to identify seizures. Using EEG big data, an Internet of Things-based optimized deep learning for seizure prediction was proposed. Using EEG data from five epilepsy patients, an adaptive structure of a multi-layer back-propagation network was developed for automated epileptic episode identification. The use of fast Fourier transform (FFT) and auto-regressive based features to wavelet neural networks classifiers resulted in a reliable classifier design [9]. The robust characteristics gained from image-based representations of EEG spectrograms in three frequency bands (0–7, 7–14, and 14–49 Hz) were used to identify seizures. The use of EEG big data was used to suggest an Internet of Things-based optimized deep learning for seizure prediction. Using the EEG data of five epilepsy patients, an adaptive structure of a multi-layer back-propagation network for automated epileptic seizure identification was developed. Fast Fourier transform (FFT) and auto-regressive based features were used to wavelet neural networks classifiers to provide a reliable classifier design [10].

Recent supervised and unsupervised approaches for training deep spiking neural networks were reviewed, and their accuracy and computational cost were compared. Aside from CNN, current research has focused on automated epilepsy seizure detection utilising various feature extraction approaches and machine learning algorithms. Seizure detection has been investigated using characteristics such as log energy and norm entropy, sigmoid entropy, matrix determinant, approximation entropy, sample and phase entropy, and permutation entropy. The support vector machine (SVM) classifier was used to classify focal and non-focal EEG data based on many criteria [11].

For epileptic seizure classification, multiple transfer functions, training functions, and mean square error were used to determine the best configuration of multi-layer perceptrons. It is obvious from the literature that no research has been offered for the categorization of multi-class seizure types in the presence of non-seizure EEG data that have yielded satisfactory classification findings. As a result, this paper proposes a CNN-based system for categorizing EEG-derived seizure types that uses transfer learning and extracts visual characteristics using pre-trained networks [12].

3. DESIGN METHODOLOGY

Machine learning and deep learning, particularly convolutional neural networks, are in increasing demand for multi-class seizure type categorization. As we all know, manual evaluation of long-term electroencephalogram recordings, which might last for days or weeks, is a time-consuming operation. Special focus must be given to the creation of an automated approach for categorizing multi-class seizure types. As a result, rather of employing motor symptoms, degree of awareness, or video EEG, we used EEG alone to identify seizure types in this study.

3.1 EEG SIGNAL DATASET

We are using EEG signal databases in this study to make our hybrid model more resilient to variations in signals associated with brain disorders. The Massachusetts Institute of Technology collaborated with Children's Hospital Boston to create our database. The EEG signals from various pediatric subjects related to mental impairments and diseases are recorded in the database obtained from Children's Hospital Boston. These people had their brain diseases defined in order to see if they were candidates for surgical resection. They were kept under strict surveillance for a few days before being taken off their anti-psychotic drugs. These recorded EEG signals were divided into 23 occurrences by 22 people, 5 of whom were men between the ages of 3 and 22 and 17 of them were women between the ages of 1.5 and 19. In the same female subject, case CHB-001 and case CHB-021 had a minimal age difference of 1.5 years. Specifics such as the gender and age of each subject may be found in the file SUBJECT-INFO.

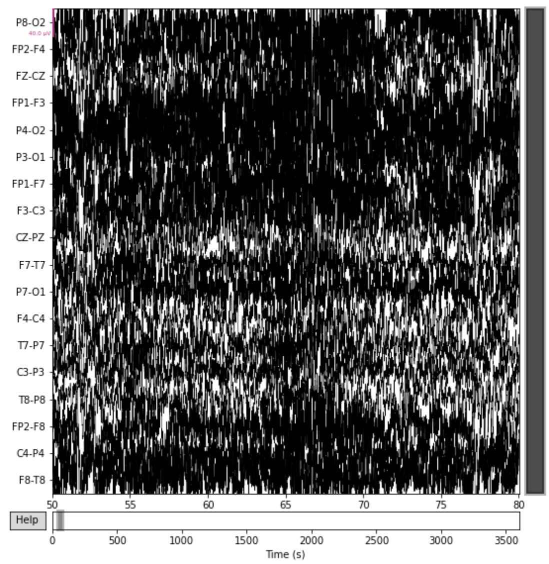

Figure 1 : EEG Signal from Signal Dataset for CHB-007

For a single pediatric subject, the Cases diagnosed for a given time comprise between 9 and 42 files with the extension .edf. Due to hardware limits, there was an unrecorded signal gap of 10 seconds or less between consecutively numbered .edf files. In the great majority of cases, EEG signals are recorded for one hour. Although, with case CHB-010, we recorded signals for two hours and four hours, and with cases CHB-006, CHB-009, CHB-007, and CHB-023, we recorded signals for four hours. Cases of Brain Disorder were kept on file for a short time. The majority of our research focuses on mental illnesses and disabilities. All of the signals were sampled at 256 samples per second with a 16-bit resolution. The majority of these files have 23 EEG signals, with a few having as many as 24 or 26. Case CHB-004's last 36 files include ECG signals and disturbances, whereas case CHB-009's last 18 files contain a vagus stimulation signal. Other signals were recorded in a few records as well. To construct an easy-to-read display format from the EEG signals, a total of five fake signals were utilised, but these false signals are fully ignorable.

3.2 SIGNAL PREPROCESSING

The raw EEG signal collection is usually deemed impure for feature extraction because it contains noise, distortion, or interference from non-cerebral sources. These non-cerebral sources are either biological or environmental variables that misinterpret brain activity, causing mental diseases to be misdiagnosed. As a result, we preprocess these signals in order to improve the quality of the features recovered. To eliminate undesirable noise from the signals, we use a number of signal processing techniques such as high pass filtering, notch and fixed linear filtering, line noise reduction interaction, and referencing.

The notch filtering technique is used to eliminate line interference noise when the data collection model for EEG signals is insufficient to lower frequencies higher than 50Hz. Signals over a cutoff frequency are passed via high-pass filtering, while noises below the cutoff frequency are attenuated. The amount of attenuation applied to each frequency is up to the filter designer. A high-pass filter is often modeled as a linear time-invariant system. To eliminate line noise, data segments are fitted with sine and cosine filters adjusted to their corresponding interference frequencies. The estimated signal components are then subtracted from the total signal. The DFT filter was employed to filter the 50 Hz component of the synthetic test signals. Abnormal amplitudes, lack of connectivity with other channels, lack of prediction by other channels, and extremely high frequency sounds are among the four fundamental characteristics used to later identify noisy and outlier channels.

From a system perspective, we study the EEG signal connected to the locations from a human brain network parcellation to understand how it influences the effect of EEG reference. As a result of our simulation, the scalp EEG was constructed using vertices equally spread among eight large-scale brain networks. The visual, somatomotor, doors-ventral attention, limbic, front-parietal, default, and deep brain areas are among the brain networks. The distribution of the most sensitive and neutral electrodes for each network was calculated using the lead-field matrix. Before we can estimate the true signal mean, we must first detect and interpolate faulty signals.

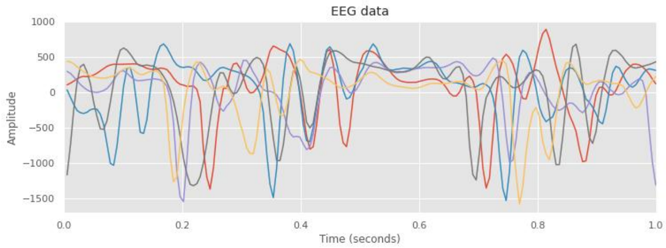

Figure 2 : EEG Data Converted to Time-Series Data Domain

Large amplitudes and lack of connection with any other channel, lack of prediction by other channels, and extremely high frequency sounds are all features that can be used to identify outlier channels later on. Apart from that, we seek for channels with NaN (not-a-number) data or lengthy periods of time with small or no values. The spherical parameter of EEGLAB's eeg interp function is utilised for channel interpolation. This function employs Legendre polynomials up to degree 7. By comparing it to the v4 option and two other spherical interpolation functions, including the one used in RANSAC, this interpolation approach was put to the test.

3.3 NETWORK ARCHITECTURE

One of our aims is to construct a hybrid model for identifying different forms of epileptic seizures using machine learning and deep learning technologies. In the current work, the dataset's distinguishing properties were used to construct a trustworthy 3D-CNN model. The goal of this study is to see if the EEG dataset acquired is sufficient for simply distinguishing healthy people and those who have been diagnosed with various types of mental seizures and impairments in connection to their anti-psychotic drugs. We're particularly concerned about the usage of specific types of electrodes capable of generating such disparities. Furthermore, we are worried about the relationship between the severity of the condition as determined during hospitalizations and the severity findings as measured by our model.

We attempt to categorize EEG signals into distinct mental classes with mental illnesses such as Myoclonic Seizure, Tonic–Clonic Seizure, Clonic Seizure, Atonic Seizure, Tonic Seizure, and their severity based on the extracted characteristics. This design uses a 10 fold trained 3D-convolutional neural network and an ensemble random forest algorithm to identify distinct mental ailments, with regression used to determine the severity of each mental condition. The VGG-19 learning model, which takes an input of 2D frequency time characteristics and represents volumetric data, is thought to be the most powerful. We adjust a variety of parameters, including reaction time, acquisition time, frequency bands, electrodes, and time-frequency representation, in order to emphasize the statistically significant difference between the replies in the two datasets.

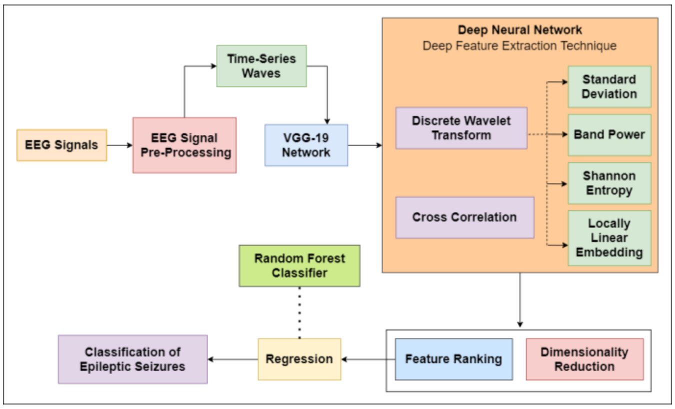

Figure 3 : Architectural Diagram for the Proposed Architecture

The RGB spectrogram of 224 × 224 pixels is sent into the VGG-19 3D-Convolutional Neural Network. The model accepts an RGB input with a range of 0-255 pixels in the pre-processing layer and subtracts the mean image value from the train dataset. The photos are pre-processed and then passed via weighted layers. We used slacked convolutional neural blocks to pass these pictures from the training dataset. This design has a total of 19 layers, sixteen of which are convolutional blocks and three of which are completely linked. This network has a maximum of five pooling layers, each having 4096 channels and 100 convolutional layer labels. The last layer is made up of completely linked SoftMax layers that are utilised for categorization. We extract discrete wavelet transform and cross correlation information from the spectrogram using a convolutional neural network.

The aberrant EEG waveform is present in all disorders and is a frequent feature of the EEG signal. The epileptiform pattern and the non-epileptiform pattern are the two types of aberrant EEG waveforms. Spike and sharp wave epileptiform pattern, which can be noticed in sleep disturbance and epilepsy patients. The waves reveal focal slow waves, diffuse slowing, and asymmetry in amplitudes and frequency for the non-epileptiform pattern. On the other hand, the methods used to analyse the signal vary based on the disease. The Fast Fourier Transform or Short Time Fourier Transform is used to investigate EEG waveforms from sleep disorders and epilepsy. For a better result in discriminating between the control and autistic groups, it is proposed that the analysis be focused on the specific frequency and on the spectrum per channel.

To categorize and grade the severity of diseases, the Random Forest ensemble approach is utilised. Random forest is an ensemble machine learning technique. This machine learning approach is likely the most widely used because of its outstanding or excellent performance across a wide range of classification and regression predictive modelling applications. It's also straightforward to use, with only a few key hyper-parameters and reasonable rules for modifying them. The Random Forest Ensemble technique may be used to find local linkages, and higher-level features can be described as composites of lower-level connections. Random Forest Ensemble can also be used to indicate dimensional significance. The main purpose of the Random Forest Ensemble approach is to exploit spatial correlations between various signal properties.

4. RESULT AND DISCUSSION

In this study, CNN was implemented successfully using scalp EEG for automated multi-class seizure type classification. The study was conducted using transfer learning and extract image features approach using a ten fold classification method. Both the approaches performed better for five class classification problems. We have performed a comparison between both the methods to identify the ideal model for seizure type classification. The best results from each pre-trained network were taken into consideration for comparison. The proposed method showed the highest classification accuracy of 93.25% and 98.40% using transfer learning and extract image features approach respectively. Comparison results showed that extract image features approach outperformed transfer learning approach in terms of classification accuracy and computation time.

Table 1 : Performance Evaluation Metrics for Proposed Model

Performance Evaluation Metrics				
Number of Epochs	Classification Metrics		Error Metrics	
	Accuracy	Precision	MAE	RMSE
0-99	0.9898	0.9854	7.32	25.43
100-199	0.9876	0.9821	7.89	26.32
200-299	0.9845	0.9878	8.56	28.78
300-399	0.9867	0.9863	8.67	24.90
400-499	0.9834	0.9870	9.98	30.23
500-599	0.9767	0.9865	9.21	31.77
600-699	0.9789	0.9855	9.46	32.99
700-799	0.9778	0.9867	8.87	29.54
800-899	0.9793	0.9788	8.54	30.43
900-999	0.9867	0.9844	8.44	33.78
Overlapped	NIL	NIL	NIL	NIL
Normal EEG	0.9890	0.9788	9.67	25.56
Abnormal EEG	0.9899	0.9854	9.87	27.56
Average	0.9821	0.9834	8.69	34.23

Using our VGG-19 based feature extraction and Random Forest ensemble model, we employ ADAM's optimizer to train our classification-based models (Adaptive Moment Estimation Algorithm). At the beginning and conclusion, we employed a 0.001 learning factor with decay rates of 0.9 and 0.999, respectively. The ADAM optimizer's role is to keep track of the parameters of the recommended architectural network. By increasing the network's coverage and bringing it closer together at a faster rate, ADAM's optimizer can improve the training process' efficiency. We utilised a batch size of 32 and a fold factor of 10 folds for the recommended model. On the fully convolutional layer, we set the dropout value to 0.5 to avoid overfitting and promote generalization. The network has achieved a convergent state after 40,000 iterations with 1000 epochs. While calculating the epochs, the iterations over the whole training dataset were referred to as epochs. We randomly divide the EEG signal dataset into 10 equal groups for training and testing using a 9:1 split. This approach has been tried ten times, with the accuracy score for each fold being thoroughly examined.

Table 2 : Performance Evaluation Metrics for Classification Model

Seizure Category	Performance Metrics			
	Specificity	Sensitivity	Accuracy	Precision
Tonic Seizure	97.89	96.78	97.89	97.65
Atonic Seizure	96.32	97.55	96.34	97.45
Clonic Seizure	97.56	97.90	97.98	97.43
Tonic–Clonic Seizure	90.44	91.12	91.22	91.56
Myoclonic Seizures	92.31	93.54	92.69	93.65

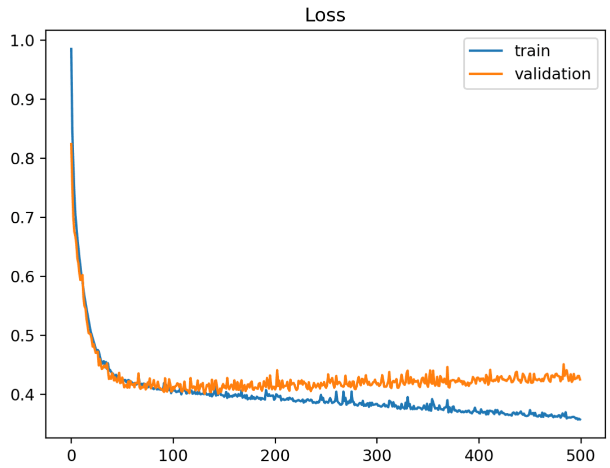

Figure 4 : Loss Curve for Proposed Model

In addition, we used IBM's SPSS 16.0 version software to do a statistical analysis on the data. We use categorical chi-square tests and continuous t-tests with independent samples to assess geographic and clinical variables between groups. To examine if there were any changes between the conditions, a paired t-test was used. The two-tailed test was used to obtain P values, with a significance level of p0.05, as well as the false discovery rate (FDR) and Bonferroni correction. Pearson's r coefficients, a sort of correlation coefficient, were used to analyse the associations. On the testing dataset, classification and precision accuracy are calculated and used to evaluate model performance. The VGG-19 model's feature extraction findings have an impact on model performance. When attempting to estimate the accuracy of the Normal EEG and Abnormal EEG classes at random, it yields a 50% result, whereas it yields a 20% result for other classes such as depression, schizophrenia, Alzheimer's, epilepsy, and sleep disorder. These accuracies were used as baselines to assess model performance over yield accuracies. For detecting true positives, false positives, and irrelevant discoveries, we calculate the accuracy and recall values of our model.

Figures 4 and 5 show the training and validation accuracy and loss curves for the classification model, respectively. The loss curve suggests that the learning curve between the overfit and underfit models is a fair fit. On the training dataset, the model loss will always be lower than on the validation dataset. As a result, the graph has a good generalization gap, making our model reliable and accurate. In comparison to previous models, the model has higher sensitivity, specificity, precision, and accuracy values.

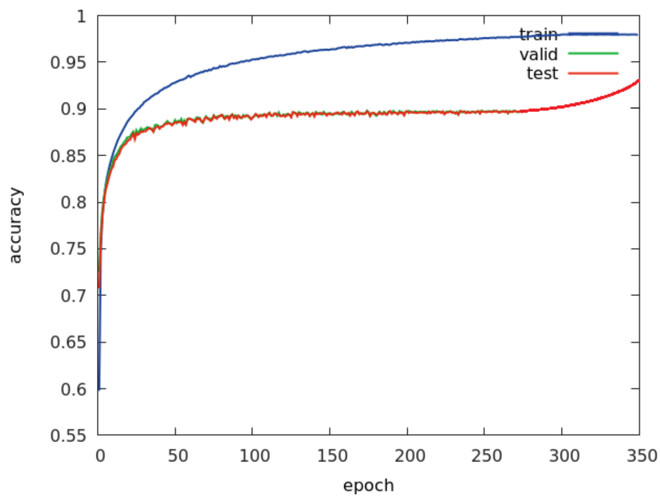

Figure 5 : Training, Testing and Validation Curve for Proposed Model

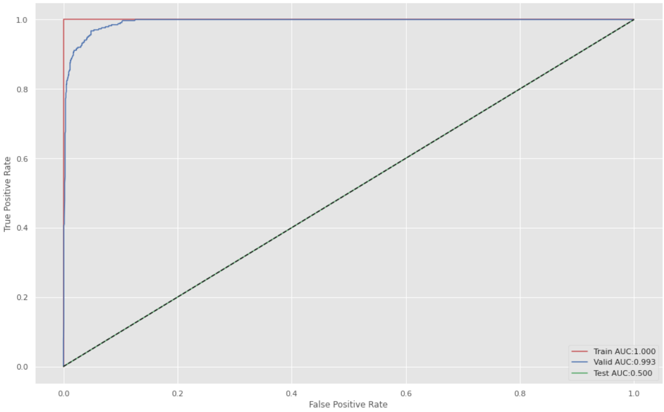

Figure 6 : AUC Curve for Proposed Model

The Accuracy Profile Cumulative Figure 5 shows how a curve is used to visualize the categorization of classes and analyse discriminating power. The y-axis represents positive classification results, while the x-axis represents the cumulative number of a classifying parameter. The CAP curve percentage for Tonic Seizure and Atonic Seizure runs from 85-90 percent, making it a very excellent classification model, but the CAP curve for Clonic Seizure and Tonic–Clonic Seizure ranges from 75-80 percent, making it a decent model.

5. CONCLUSION

This study proposed a five class classification problem to classify seizure type using CNN. The EEG time series were converted into a spectrograms stack to feed as input for CNN. The algorithm was evaluated using transfer learning and extract image features using the ten pre-trained networks. The proposed method showed the highest classification accuracy of 93.25% and 98.40% using transfer learning and extract image features approach respectively. Comparison results showed that extract image features approach outperformed transfer learning approach in terms of classification accuracy and computation time.

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