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A Machine Learning Model for Cerebral Palsy Disorder Detection in Integration with Hybrid Optimization

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Abstract—The development of effective treatments for Cerebral Palsy (CP) can begin with the early identification of affected children while they are still in the early stages of the disorder. Pathological issues in the brain can be better diagnosed with the use of one of many medical imaging techniques. A unique Machine Learning (ML) model that was built to identify CP disorder is presented in this paper. The model is intended to assist in the early diagnosis of CP in newborns. In this study, the brain Magnetic Resonance Imaging (MRI) images dataset was collected followed by preprocessing. The proposed model was constructed by combining three CNN models, specifically VGG 19, Efficient-Net, and the ResNet50 model, to extract features from the image. A Bi-LSTM was utilized as a classifier to determine the presence of CP and finally, the proposed model was used for training and testing. The outcomes established that the suggested model accomplished an accuracy of 98.83%, which is more than the accuracy accomplished by VGG-19 (96.79%), Efficient-Net (97.29%), and VGG-16 (97.50%). When the suggested model is compared to other models that have been pre-trained in the past, the accuracy scores seem to be much higher.

Keywords—*Cerebral Palsy, Machine Learning (ML), Deep Learning (DL), MRI, Disorders.*

I. INTRODUCTION

Cerebral palsy (CP) is a collection of impairments affecting mobility, posture, and motor function. These problems are caused by non-progressive injuries to the immature brain [1]. It is advisable to identify CP or high-risk CP early on in childhood so that early targeted therapies and support services can be immediately available. There are two separate ways that CP can be detected early, according to guidelines published in 2017 by Novak et al., [2]. One way is for babies who have newborn-detectable risk factors, like being born prematurely, having a low birth weight, or having hypoxic-ischemic encephalopathy, to be checked for CP before they are 5 months old. This can be done with a thorough history and physical examination, as well as with neonatal MRI, General Movement Assessment (GMA), and the Hammersmith Infant Neurological Examination (HINE) [3]. Second, between the ages of 5 and 24 months, infants who do not have any known neonatal risk factors but do have infant-detectable risk factors, such as delayed motor milestones during the infantile period, should be evaluated for CP using a battery of tests, including standardized motor assessments, the HINE, and neonatal MRI [4,5].

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Clinical assessment of symptoms and disorders remains the primary method for CP diagnosis (Table 1). The more quickly these patients get a proper diagnosis of CP and begin treatment, the higher their chances of a full recovery with fewer long-term effects on their lives. Figure 1 displays the many forms of CP. In the end, CP is a complex disorder with several risk factors, the majority of which are not easily preventable. When it comes to paediatric CP, the worldwide agreement among industry professionals is that the best course of action is early diagnosis and treatment. Children have a higher chance of making a full recovery if they get early interventional therapy, which can significantly slow the progression of their illness [6,7].

II. LITERATURE REVIEW

The study is conducted of the previous works and found gaps based on CP Disorder Detection using ML.

Sabater et al. The suggested model produced the most promising results on the CP-PAIN dataset, with an accuracy of 62.67% and an F1 score of 61.12%. The study highlights the necessity of future research and demonstrates the possibility of technological adaptation for healthcare applications [23].

Mohan et al., Outperforming previous methods, the model achieves a remarkable 96.4% accuracy in predicting CP from brain scans. The model's accuracy is confirmed by comparing it to clinical evaluations and doing thorough cross-validation [24].

Berton cell et al. The proposed model implements Logistic Regression (LR). Accuracy, sensitivity, and specificity were all above average for the top multivariate model, which achieved 84%. The long-term goal is to use and improve the model with thousands of patients [25].

Gao et al. The proposed DL-based motor assessment model (MAM) produces results of the external validation show that MAM performs well, with an AUC of 0.967. The creation of an ML-based GMA automation system has the potential to increase diagnosis accuracy, streamline access worldwide, and completely transform early CP screening [26].

Ramadhan et al. proposed a CNN based model and evaluated in terms of sensitivity, accuracy, precision, and F1 score. Possible applications of the proposed method in the future include solving problems involving category categorization, such as distinguishing between paraplegic and pyramidal forms of CP [27].

Li et al. A Knowledge-based RNN (KBRNN) model is proposed. After receiving enough training using the 100% train-set, the KBRNN improves its diagnostic accuracy to 83.12% from 79.31% while using just the information derived from the KG based on pre-set. Train KBRNN using a significant quantity of labeled EMR to increase its performance beyond the existing model [28].

Cheragh et al. The suggested method obtained IoU values of 0.99, recall of 0.98, and an average dice score of 0.99. There are no other diagnosis or scoring options available, and the job set just includes segmenting the bone pieces [29].

Xue et al. The actigraphy algorithms were average 86-89% accurate, 88-92% sensitive, and 70-75% specific in children without CP. Research in the future can look at ways to enhance the quality of sleep for children with CP and make actigraphy algorithms more sensitive and accurate in identifying their sleep patterns [30].

There is a challenge in detecting CP in newborns because the symptoms of the illness do not become apparent until a year after the child is born. This results in a reduction in the likelihood of achieving better outcomes from therapy when compared to the situation in which the condition was diagnosed earlier. However, conventional diagnostic approaches often depend on individual assessments and can be time-consuming, which can result in delays in both the diagnosis and the treatment of the condition.

III. Proposed Methodology

The proposed methodology flowchart based on the study and design of an optimized prediction model for CP disorder using ML techniques (Figure 2). The first step involves gathering comprehensive data on patients diagnosed with CP. This data can be collected from hospitals, clinical trials, and healthcare databases. The dataset needs to include several characteristics, including demographics, health history, genetics, clinical test findings, and other pertinent health markers. Cleanup and preprocessing are necessary steps after data collection to make sure the data is ready for analysis. As part of this process, we address missing values, standardize numerical data, encode categorical variables, and eliminate outliers that can distort the result. Feature extraction refers to the steps used to turn unstructured data into trainable model features. In this stage, we will determine which factors are most important for CP prediction. For feature extraction, they used a TL model, such as VGG-19, Efficient-Net, or VGG-16. The next step is to divide the prepared dataset into two primary sets: one for training purposes and another for testing. A 50:50 split is the norm for data distribution. The current step is to find the optimal model for CP prediction using ML techniques, such as Bi-LSTM using TL approaches. Based on the evaluation metrics, they evaluate the efficiency of various models. The best model for predicting CP can be found by comparing these models based on evaluation metrics.

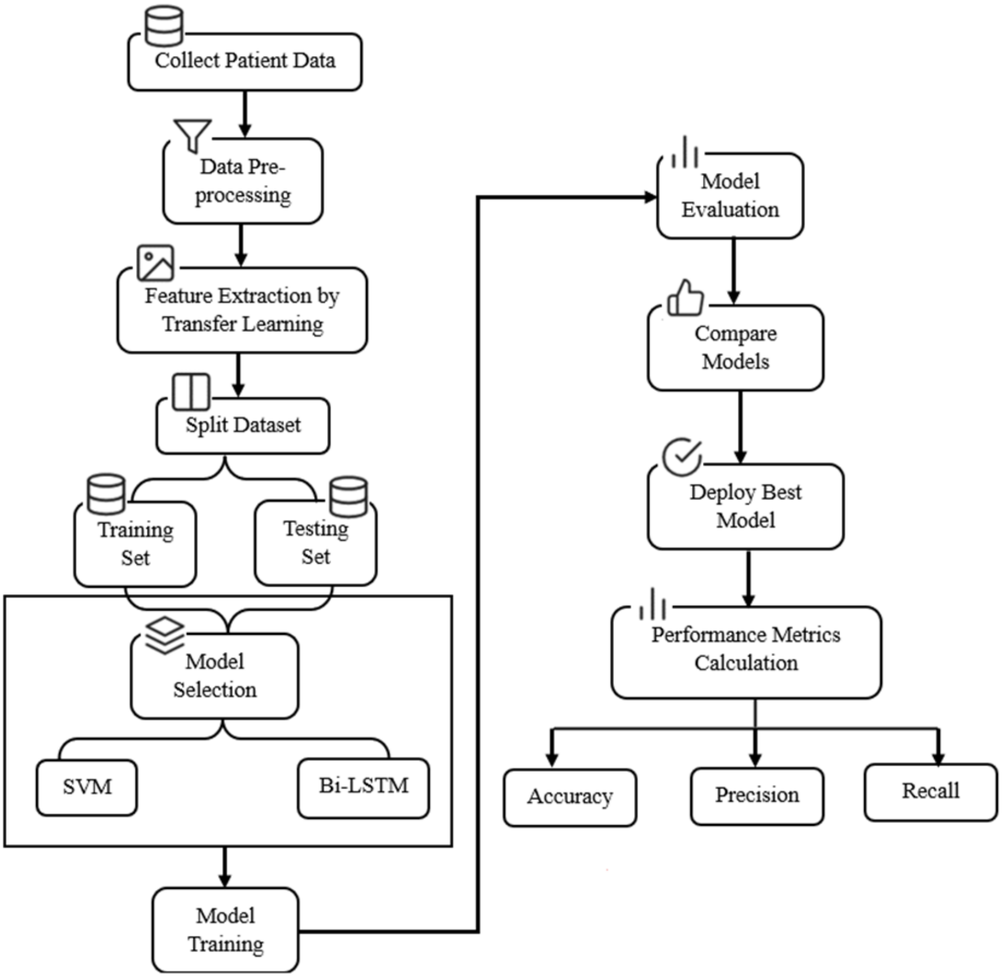


Fig.1. Flowchart of proposed work

A. Data Collection

This phase included the collection of data that was used for training and testing the suggested model. It was necessary to have two distinct classes of MRI images of the brain: one class was for MRI images of the brain for normal individuals, and the other class was for MRI images of the brain for those who had CP. Through the use of the Kaggle website, 98 pictures were acquired from the brains of typically functioning individuals. As for the images of the brains of individuals who have CP, there was no data set available on the internet, therefore they were taken from Santi Hospital in Agra from persons who have CP. There are a total of 65 photographs in this collection. There are examples of normal MRI brain images as well as MRI images of CP on display in Fig.2.

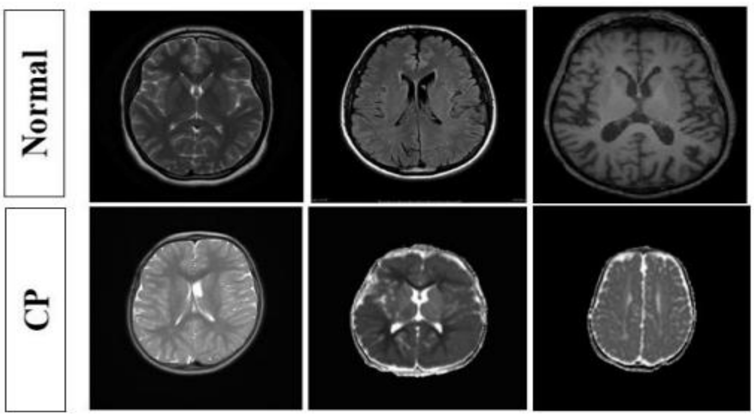


Fig.2. MRI brain dataset

B. *Data Pre-processing*

The data are being prepared for the categorization model at this stage of the process. This stage is comprised of two stages, which are the splitting of the data and the augmentation of the training data phases.

- Data Splitting

The dataset is now divided into two sections, one for training and the other for testing. The model is trained using the training dataset, and its efficacy is assessed using the testing dataset. When using ML, it is common practice to use a dataset that was not used during training to test the model. The dataset plays a vital role in training and evaluating the model. The MRI images are the focus of this study. The MRI images in the dataset are of two types: one is for individuals with CP (abnormal), and the other is for those without C (normal). They used Kaggle to get both kinds of MRI images. One type is used for training and the other for testing, and each sort is split into two groups. Part of this research included dividing the dataset in half so that 50% could be used for testing and 50% for training.

- Data Augmentation (DA)

Data augmentation is a method for improving the quality of data included in a dataset. It is also used to create new pictures that are derived from existing ones. DA is now the default in ML due to its ease of use and the fact that ML's model training approach demands a large amount of data for good model training. This study makes use of both rotational and flipping augmentation techniques. Fig.3. 4 (a) shows the original image with the DA applied to it; Fig.4. (b) shows the rotation process DA technique, and Fig.3. (c) shows the flipping process DA method.

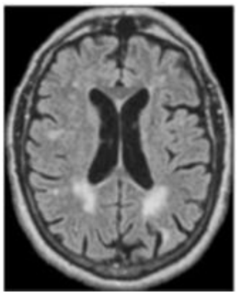


Fig.3 (a) Original Image

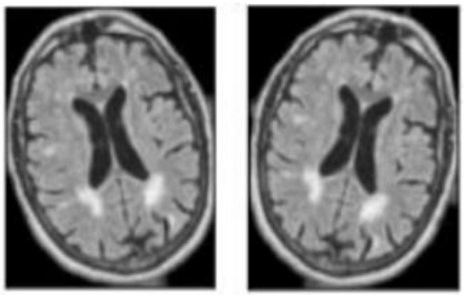


Fig.3(b) Rotational Image

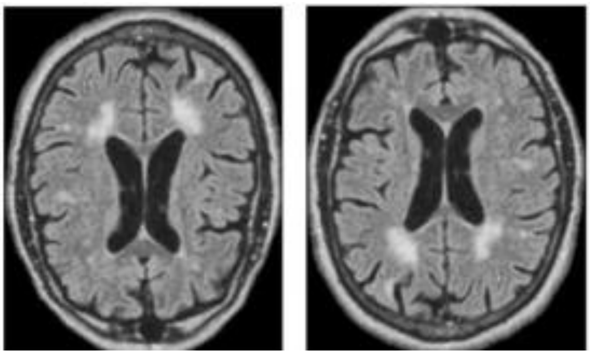


Fig.3 (c) Flipping Image

C. *Transfer Learning (TL)*

TL is an essential and effective method for training a network with a small amount of data [32]. In this study, they use VGG-16, VGG-19, and Efficient-Net model for CP detection.

- Efficient-Net

In 2019, a family of deep CNN architectures called Efficient-Net was released. After that, it has shown breakthrough performance on several computer vision applications. With a compound scaling strategy, Efficient-Net optimizes the network's depth, breadth, and resolution all at once, resulting in great accuracy and computing efficiency. The two main networks of Efficient-Net are the backbone network, which does feature extraction from input images, and the head network, which does the final classification [33]. To capture input spatial and channel-wise correlations, the backbone network includes a mix of mobile inverted bottleneck convolutional layers and squeeze-and-excitation (SE) blocks. For the last categorization, the head network employs fully linked layers in conjunction with global average pooling. Figure 5 shows the framework of the Efficient-Net method.

D. Performance Metrics

To evaluate the accuracy of the proposed classifiers' predictions, six metrics were used, all based on the number of True positives (TP): This indicates that a person has been categorized as having CP; In a true negative (TN) test, a healthy individual is considered to be in good health. In the case of a false positive (FP), a healthy individual is mistakenly identified as having CP. In the case of a false negative (FN), an individual with CP is mistakenly identified as being in good health. Tab.1. shows the confusion matrices of binary classification.

Tab.1. Confusion matrices

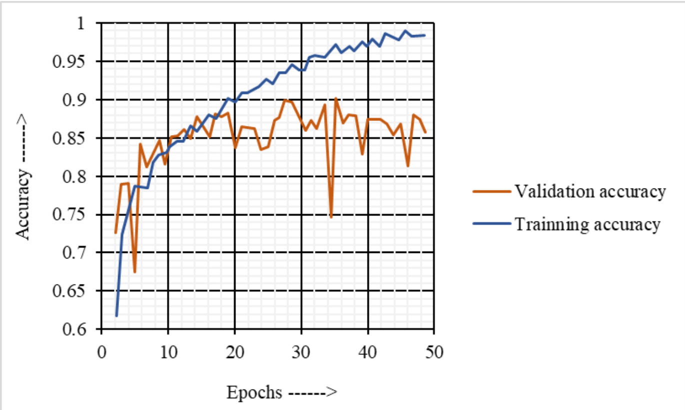
	Actual positive	Actual negative
Predicted positive	True Positive (TP)	False Positive (FP)
Predicted negative	False Negative (FN)	True Negative (TN)

IV. Result and Analysis

The data set that was used in the process of putting the suggested model into action and evaluating its effectiveness is offered in this paper. The model is divided into two parts: the first part deals with the results of the suggested model's training phase, where the training data is used, and the second part deals with the results of the evaluation phase, where the test data set is used to test the performance of the proposal method that was trained with the training data.

A. VGG-19

The batch size was set to 32, the learning rate was set to 0.001, the optimizer was set to degrade and lastly, categorical cross-entropy was chosen as a loss function. They were able to achieve the best set of model training parameters. They trained and verified the VGG-19 model for a total of 50 epochs, and the graphs that represent the accuracy of the model are shown in Fig.4.



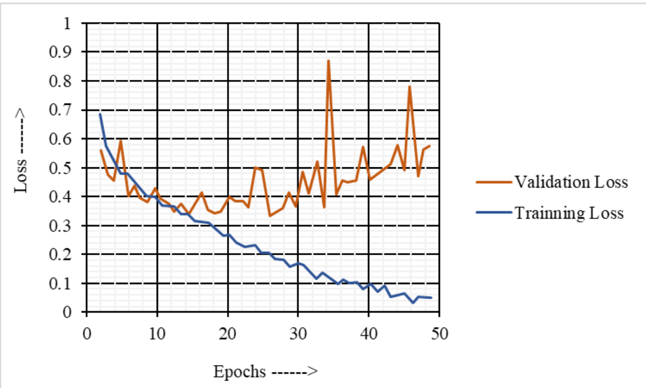


Fig.4. Accuracy of the VGG-19 model

Fig.5. Loss of the VGG-19 model

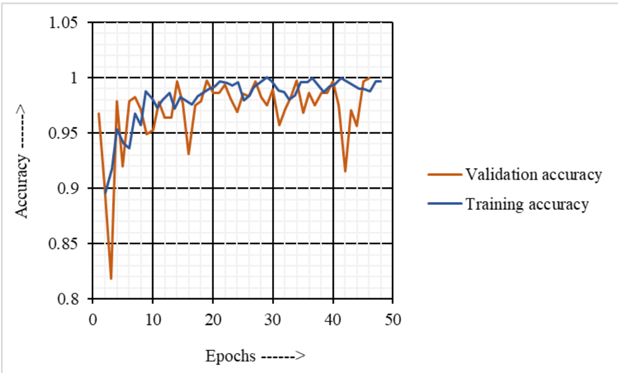
A representation of the VGG-19 model loss at each epoch is shown in Fig.5. So, 19 of 20 individuals were thought to have CP, whereas 19 of 20 were thought to be normal. There is a report on the categorization using Efficient-Net in Tab.2.

Tab.2. The result of VGG-19 model

S. No.	Performance Metrics	Result	Recall
1	Accuracy	97.50%	97.8
2	Precision	95.25%	93
3	Recall	100%	92
4	F1-score	97.56%	77.4

B. *Efficient-Net Model*

Fig.6. shows the results of efficient-Net's validation and training/learning accuracies. The training accuracy, shown by the blue line, grows as the epoch count rises and reaches 100% after 50 epochs. The validation accuracy is shown by the brown curve, which starts at 96.56% and rises to 98.02% after 50 epochs. They stopped training after 50 epochs due to overfitting in the learning curve. Optimal training/validation accuracy was achieved by fine-tuning the number of training epochs.



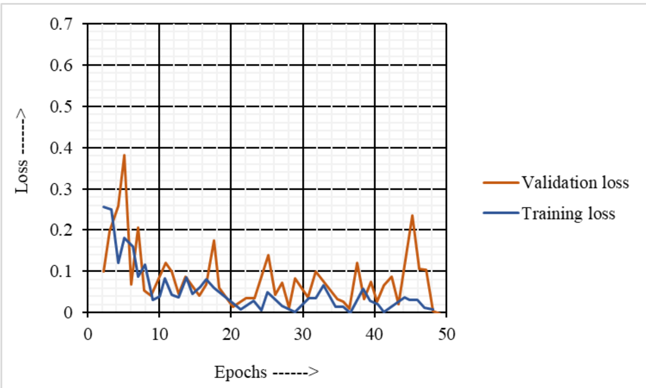


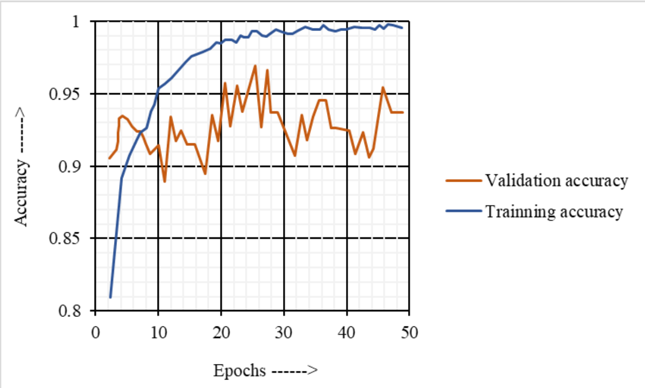
Fig.6. Accuracy of the Efficient-Net model

Fig.7. Loss curves of the Efficient-Net model

The training and validation loss for the Efficient-Net model is shown in Fig.7. A score of 0.0 would imply that the whole learning process was outstanding and there were no errors observed. After 50 epochs, the training loss reached 0.0030 and the validation loss, which started at 0.110 and decreased to 0.01, both decreased steadily with increasing epoch count.

C. *Result of Proposed Model*

The model that was suggested had been executed by using a VGG 19 and Efficient-Net model. This meant that every MRI image that was included in the training data set was processed by each of the available models. The results of an Efficient-Net model were 513 feature maps for each image, and the results of a VGG 19 model were 2062 feature maps. Following the integration of the feature map for every model, a 3047 feature map is created for every image.



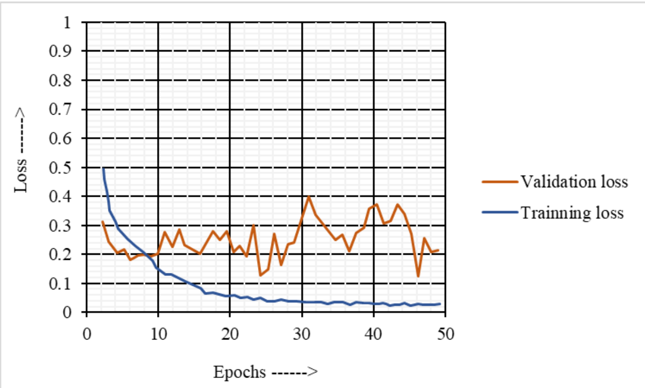


Fig.8. Accuracy curves of the suggested model

Fig.9. Loss curves of the suggested model

The suggested model (VGG 19 and Efficient-Net) was built using weights from training each model on the training data set and the ImageNet dataset. Adam, the optimizer, teaches the model with a 0.4 learning rate and a hinge loss function. To make the model train more accurate, the training information goes through 50 iterations. Next, the model was tested using the MRI testing dataset, which includes 32 MRI images. Figure 15 shows the accuracy curve, whereas Figure 16 shows the loss curve. Because the validation curve is continually rising and falling while the training loss is constantly reducing, the training and validation curves show that the model started to overfit beyond a certain point. Due to the limited size of the training and validation sets, the model is unable to extract features for all possible scenarios.

D. Comparison of the Suggested Model with VGG-19 and Efficient-Net

To predict CP, the VGG 19 and Efficient-Net models were utilized with a similar dataset that was used in the suggested model. The results of these models were compared with the findings of the proposed model. The accuracy that is acquired with the use of the VGG-19 model through the utilization of the TL technique is 96.79%. The accuracy that is acquired with the use of the Efficient-Net model through the utilization of the TL technique is 97.29%.

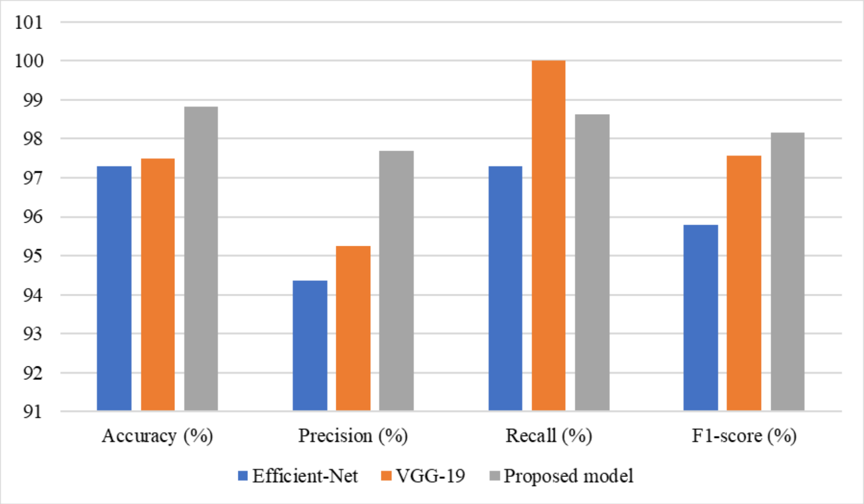


Fig.10. Graph of comparison of the Suggested Model

The accuracy that is acquired with the use of the VGG-19 model through the utilization of the TL technique is 97.50%. When applied to the same dataset, the suggested model attained an accuracy of 98.83%. Figure 18 is a bar chart that illustrates the comparison of all the metrics between VGG-19, Efficient-Net, and the suggested model. Table 8 presents the results of this comparison.

Tab.3. Comparison of the suggested model with VGG-19, Efficient-Net, and VGG-16

S.No.	Metrics	Efficient-Net	VGG-19	Proposed model
1	Accuracy (%)	97.29	97.50	98.83
2	Precision (%)	94.36	95.25	97.70
3	Recall (%)	97.29	100	98.64
4.	F1-score (%)	95.80	97.56	98.17

V. Conclusion

CP is a group of permanent movement disorders that appear in early childhood, affecting posture, balance, and motor functions. Early and accurate detection of CP is crucial for timely intervention and management. This study presents a novel machine-learning model designed to detect CP disorder. The suggested model uses a large dataset consisting of brain MRI scans. Missing data is executed, features are normalized, and image quality is enhanced using various preprocessing approaches. The Bi-LSTM is a supervised learning algorithm used to train the ML model that combines feature extraction approaches. They used pre-train CNN models such as VGG-19 and Efficient-Net. Standard measures including F1-score, recall, accuracy, and precision are used to assess the model's performance.

The experimental results show that classification accuracy of 97.29% when applying the Efficient-Net model, 97.50% when applying the VGG-19 model, and 98.83% when the two models were combined with Bi-LSTM as a classifier. Thus, when the two models are combined, the extracted features are further improved. The accuracy of the model and dataset expansion to include a more varied patient group will be the primary goals of future studies.

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