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Predictive Healthcare with Integrated EEG and Facial Emotion Recognition using Deep Learning and Transfer Learning

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***Abstract*— The main objective of this innovative project is to transform modern-day neurological healthcare, additionally pairing and synchronizing EEG signals with facial recognition information for efficient detection of neurological sicknesses. Machine learning algorithms are used for promptitude, ensuring rapid interventions during the course of the disease, and for careful and efficient balancing of the patient's conditions. The system based on the above-discussed approach is characterized by a patient-centered nature ensuring that trust and ethical liability are the top priorities of the developed model. Such system supported by multiple machine learning algorithms also increase the accuracy of the diagnosis, its potential for early identification, and targeted therapy, ultimately having a beneficial effect on the public health. The researches findings demonstrate that there are convincing proofs that machine learning can be used for predictive healthcare: VGG19 achieved 86.28%, Random Forest Classifier 94.48%, and for epilepsy, Random Forest and Gradient Boosting for brain tumors 92.12% and for Parkinson's disease 90.52%, respectively. Ensembled EEG analysis had the accuracy of 91.83%. Importantly, a result of 82.51% accuracy was achieved with the final decision-making process using transfer learning with the method of ensembled models and VGG19. Thus, it is possible to conclude that different machine learning algorithms are effective in predictive healthcare and can promote the progress of medical technology to benefit public health.**

Keywords—EEG, Facial Recognition, Machine Learning, Depression, Epilepsy, Brain Tumors, Parkinson's disease, Random Forest Classifier, Gradient Boosting Classifier, Ensembling, VGG19, Transfer Learning.

I. INTRODUCTION

Neurological diseases include a broad range of both physical and mental conditions and present profound disorders of human well-being [1]. Parkinson's disease, epilepsy, brain tumors, and depression all provide unique challenges ranging from a diagnosis of the motor system of Parkinson's, the recurrent seizures of epilepsy, symptoms of brain tumors such as headaches and seizures, as well as the constant anxiety and sadness of depression. The approach to these diseases varies greatly from medication and lifestyle changes to surgery and therapy. All of the previously mentioned, however, share instances of complexity and require multidisciplinary approaches [2]. Their deeply interwoven causes, whether their basis in genetics, biology, environment, or psychology, is improving the creation of treatment paradigms as well as restructuring the way the respective communities of patients are supported. A multifaceted approach to research promises to yield better results to the affected parties through gaining a more fundamental understanding of the origins of neurological diseases [3].

Neurological diseases include a wide range of symptoms, which greatly affect the lives of the patients. Motor symptoms accompany with tremors, bradykinesia, muscle rigidity and non-motor symptoms like depression and cognitive impairment can be seen in patients with Parkinson's Disease . Common presentation of epilepsy is in seizure along with an aura, confusion and loss of awareness . Brain Tumors cause persistent Headache, Seizures, Cognitive , changes and Sensory changes. At times, the symptoms result in depression [4]. The later involves persistent sadness, changes in appetite and sleep, fatigue, death recurrent thoughts. A perfect diagnosis is important to ensure timely and optimal management of each specific patients. . It also would guide a more individualized approach to managements. Such an approach in turn would enhance the quality of life of the patient.

Neurological conditions have an impact on millions around the world. Parkinson's disease between 7 and 10 million people, epilepsy affects 50 million, brain tumors afflict approximately 230,000 people every year, and depression affects over 260 million. Access to healthcare is heavily correlated to disease burden and mortality. Millions of people in India are affected by the above neurological conditions and more, while access to quality neurological care still varies so underdeveloped infrastructure and raised awareness is necessary [5].

II. METHODOLOGY

This research paper provides a clearer understanding of Parkinson's disease, epilepsy, brain tumors, and depression, their causes, symptoms, treatments, and impacts on society [6]. The current paper reports the method that has been used to analyze literature and gather empirical data to provide insight regarding these neurological diseases.

A. Dataset description

The collection includes 35,685 grayscale face pictures sized 48x48 pixels, grouped by emotions like happiness, neutrality, grief, rage, surprise, contempt, and fear. It's broken into train and test sets. Additionally, there are CSV files with recordings from 500 individuals, grouped into Parkinson's illness, epilepsy, brain tumors, and depression sections. Each participant's file contains EEG recordings sampled into 4097 data points over 23.6 seconds.

Fig. 1. Dataset [Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise]

B. Model Training and Evaluation

The dataset was evaluated for feature extraction using pre-trained CNN models such as VGG19 and machine learning algorithms, including Random Forest and Gradient Boosting, for discriminating between various subtypes of neurological diseases. Fine-tuning was performed and features were used for classification within fully connected layers. The evaluation of the model was measured through evaluation metrics and Ensembling methods were used to combine predictions for improvement in accuracy [7]. An additional average Ensembling method was utilized following all the machine learning algorithms for an improvement in classification results. A performance comparison was also involved between the facial and EEG evaluations and the VGG19 and the Ensembled model were also considered for transfer learning for maximum efficiency and applicability.

C. Model Architecture

The VGG19 architecture was proposed by Simonyan and Zisserman in the year 2014. It comprises of 19 layers designed in a very deep and uniform manner. The 3×3 small sized receptive field is used at the core of its architecture that is advantageous to improve the tangible reduction. The architecture recommended more number of layer sets with 3×3 filters followed by the 2×2 max pooling. Therefore, it is best at effective feature extraction, leading to the best performance for many applications including image classification and object recognition. Its depth and simple structure have made it a better choice for learning.

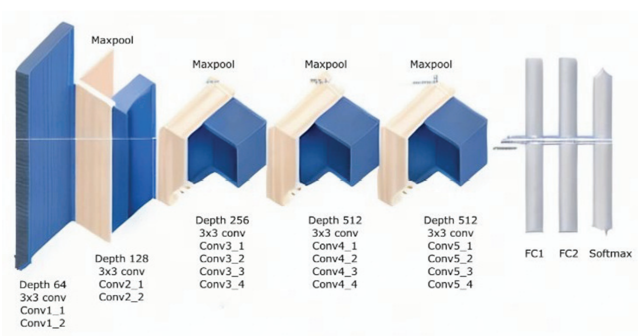

Fig. 2. VGG19 Architecture

Ensembling is the process of combining predictions from various models, such as Random Forest classifiers and Gradient Boosting Classifiers [8]. It can significantly improve the model's overall performance through a diversity of modeling. We can achieve that by averaging predictions, stacking models, or using bagging and boosting. By using Ensembling, it becomes easier to avoid the overfitting risk and capture more apparent patterns in data. Transfer learning is based on the idea of applying knowledge gained from one task to another similar one. It allows us to transfer learned representations to another model in such a way that it may reach convergence faster and demonstrate better performance in cases when the amount of labeled data is insufficient. We applied both these methods and transferred the weights from VGG19 to the ensembled model, which significantly contributed to the optimization of performance and adaptability of the latter.

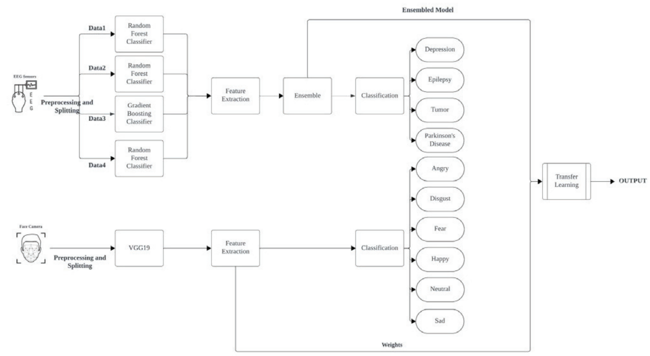

Fig. 3. Proposed Model Architecture

III. RELATED WORKS

Deep learning has seen various innovations and impacts of new frameworks on medical image analysis. Wang, Li, and Xiao introduced a deep learning framework of Multiple Genetic Syndromes Recognition by using ResNet Architecture and Transfer Learning with Cross-loss Training Method. However, the authors admitted that there were convergence issues with the deeper network. The technology is accurate by a percentage of 93.50%, which means that it will have a significant role in genetic disease diagnosis [9]. On the other hand, Jin, Wang, and He came up with a deep learning transfer technology of a deep transfer learning technology of deep facial technology to address the problem of insufficient data. It is not possible to assess the accuracy value since one was not provided. An impressive 90% accuracy raises the question of ethical data usage by participants and the fact that the dataset is relatively small for broader applications [10]. Besides, technology has also evolved in the process so that there were many improvements contributing to increased accuracy. For instance, Yu et al. presented an Automated Depression Diagnosis system using deep networks, which encode facial expressions and dynamics. The idea may not work well in real-life applications due to the computational costs, as mentioned by the authors [11]. The Deep Network achieved promising cross-user accuracy, demonstrating a high probability of diagnosing Depression Disorder. This approach incorporated Facial Identification by a systematic review and meta-analysis performance of different deep learning and machine learning networks conducted by Kong. This approach had a performance accuracy of 91% [12].

An investigation of facial expressions in Alzheimer's disease was strongly conducted by Seidl et al. Though the study was limited in terms of generalizability, the insights that the authors managed to offer have proven very valuable for Alzheimer's disease research [13]. The non-invasive nature of the EEG technology has opened numerous opportunities for diagnosis evaluation for various neurological disorders, as was shown by Salem. The accuracy level achieved was $p < 0.001$ [14]. An early depression diagnosis system based on the Ant Lion Optimization algorithm and k-NN classifier as presented by Tian is likely to produce a very impressive effect in depression diagnosis, with an accuracy of 90.70% [15]. The EEG Parkinson's disease recognition system developed by Chang basically on the attention-based sparse graph convolutional neural network has also illustrated a number of PD-related biomarkers achieved an accuracy of 87.67% [16].

Li proposed a new method for the extraction of latent factors of EEGs and their identification with the ultimate purpose of diagnosing Alzheimer's disease. The overall accuracy of the new procedure was equal to 98.10% [17]. Also, Liu developed an original method for diagnosing Parkinson's disease with the use of an EEG Brain Network. The precision value of the novel method was equal to 0.908 characteristics, which achieves particularly important results [18].

IV. Results

On the point of actual application of the suggested algorithm, it would be said that the process should commence by collecting EEG signals and facial recognition data from patients using specialized sensors and cameras. The data should be pretreated to remove noise and artifacts and initiate the extraction of important features in both data modalities. Then, machine learning models, for instance, Random Forest or Gradient Boosting, should be trained and their performance validated based on the features extracted from data sources. Afterward, ensemble models should be built to enhance the models' accuracy. In the end, the trained models should be embedded into a real-time monitoring system and clinicians should be provided with user-friendly interfaces to support their use. The system should be deployed in healthcare installations, however, it should be continuously monitored so that the models are behaving ethically and be very cautious regarding patients' privacy. For instance, it should be ensured that no pictures of faces are permanently stored on a server or shared. If found that the model can be no longer used, it has to iteratively rerun the previously mentioned procedure to enable optimal patient care.

A. *Facial Recognition - VGG19:*

One of the most significant successes in the field of deep emotion recognition is using deep learning, in particular, it is possible to speak about the capabilities of the CNN architecture named VGG19, leading to the results of the present research, which obtained an accuracy of 86.28% using VGG19 in the identification of facial emotions.

TABLE I. VGG 19 Validation report

VGG19				
Class	**precision**	**recall**	**f1-score**	**support**
Angry	0.80	0.81	0.81	73
Disgust	0.87	0.87	0.87	23
Fear	0.83	0.83	0.83	205
Happy	0.92	0.84	0.88	356
Neutral	0.86	0.86	0.86	248
Sad	0.81	0.77	0.79	259
Surprise	0.65	0.79	0.71	170
macro avg	0.82	0.82	0.82	1334
weighted avg	0.83	0.83	0.83	1334

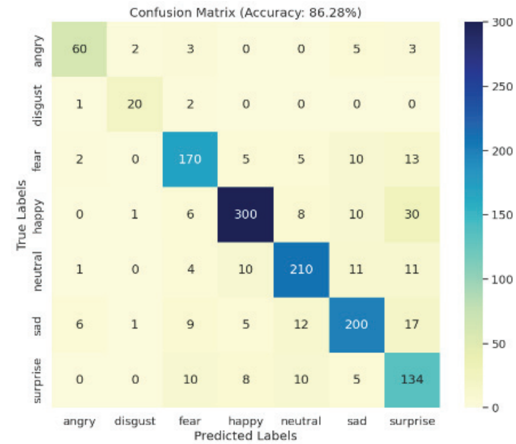

Fig. 4. VGG19 Validation Confusion Matrix

B. *EEG Depression – Random Forest Classifier:*

Prior to this, the efficacy of EEG data in epilepsy detection was explored, using a Random Forest Classifier. Due to the unique patterns detected in the EEG recordings, resulting in a high validation accuracy of 90.22%, the Random Forest Classifier proved to be a suitable method for correctly detecting epileptic seizures. This again points to the benefit of machine learning algorithms in the analysis of EEG signals to allow for increased accuracy, and therefore immediate diagnosis, of neuropsychological disorders.

TABLE II. EEG Depression Validation report

EEG Depression (RFC)				
Class	**precision**	**recall**	**f1-score**	**support**
Depressed	0.95	0.99	0.97	11207
Not Depressed	0.93	0.76	0.84	2560
macro avg	0.94	0.87	0.90	13767
weighted avg	0.94	0.94	0.94	13767

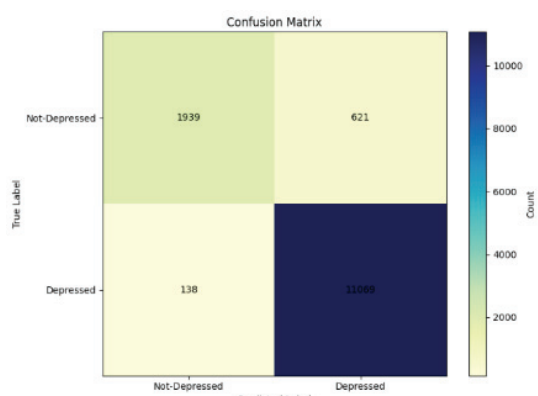

Fig. 5. EEG Depression Validation Confusion Matrix

C. *EEG Epilepsy – Random Forest Classifier:*

In the study, the Random Forest Classifier worked out well in confirmation that EEG information was valuable in the early identification of epilepsy. For this purpose, the statistical machine learning tool was in a position to interpret the unique features observed from the various EEG recorders and managed to record a fantastic validation of around 90.22%.

TABLE III. EEG EPILEPSY VALIDATION REPORT

EEG Epilepsy (RFC)				
Class	**precision**	**recall**	**f1-score**	**support**
Not Epilepsy	0.91	0.89	0.90	6985
Epilepsy	0.88	0.90	0.89	6281
macro avg	0.90	0.90	0.90	13266
weighted avg	0.90	0.90	0.90	13266

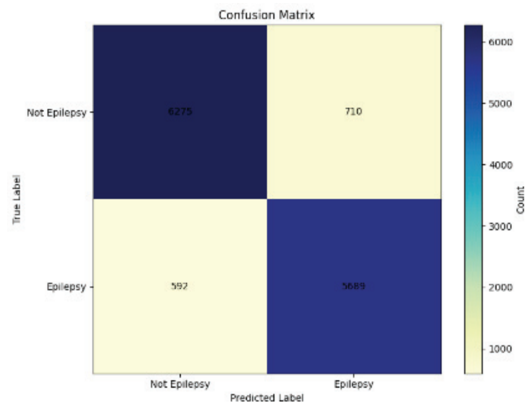

Fig. 6. EEG Epilepsy Validation Confusion Matrix

D. EEG Tumor – Random Forest Classifier:

EEG Data has been applied to the tumor detection problem with the Random Forest Classifier. Data is collected in the form of EEG recordings and the recordings are analyzed to find abnormalities that will indicate the presence of a brain tumor. The Random Forest Classifier achieved a validation accuracy of 92.12%. It can be observed that such machine learning algorithms can identify neurological diseases like brain tumors helping them to efficiently cure these diseases.

TABLE IV. EEG TUMOR VALIDATION REPORT

EEG Tumor (RFC)				
Class	**Precision**	**Recall**	**F1-score**	**Support**
Not Tumor	0.88	0.94	0.91	5574
Tumor	0.95	0.90	0.93	7693
Macro avg	0.92	0.92	0.92	13267
Weighted avg	0.91	0.92	0.92	13267

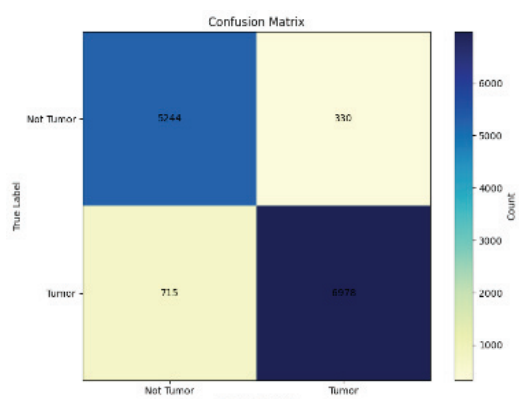

Fig. 7. EEG Tumor Validation Confusion Matrix

E. EEG Parkinson's Disease – Gradient Boosting Classifier

In transforming neurological healthcare, we have investigated the utilization of EEG data for the detection of Parkinson's disease using a Gradient Boosting Classifier. Specifically, the generated patterns on the EEG signals that illustrate the Parkinson's disease contributed to a relatively high accuracy of the validation 90.52%.

TABLE V. EEG PARKINSON'S VALIDATION REPORT

EEG Parkinson's Disease (GBC)				
Class	**precision**	**recall**	**f1-score**	**support**
Not Parkinsons	0.86	0.79	0.82	3528
Parkinsons	0.92	0.95	0.93	10099
macro avg	0.90	0.90	0.91	13627
weighted avg	0.89	0.87	0.88	13627

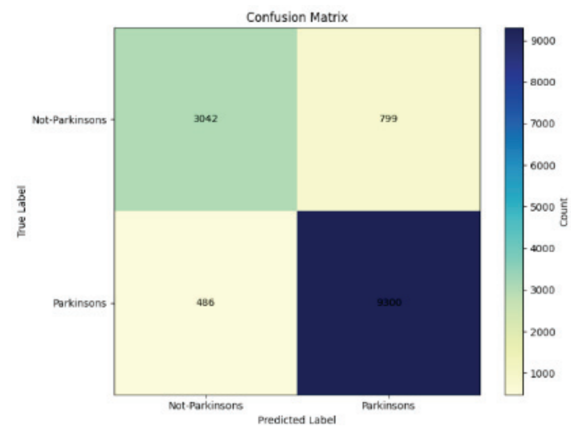

Fig. 8. EEG Parkinson's Validation Confusion Matrix

F. EEG Ensembled – Average Ensembling method

learning.

In an attempt to promote neurological healthcare, we made a study that investigated the use of EEG data analysis techniques in combination with the Average Ensembling method, the investigated approach showed impressing validation accuracy equal to 91.83% for diagnosing neurological disorders.

TABLE VI. EEG ENSEMBLED VALIDATION REPORT

EEG Ensembled (Average Ensembling)				
Class	**precision**	**recall**	**f1-score**	**support**
Normal	0.97	0.97	0.97	2854
Depressed	0.98	0.86	0.92	2851
Epilepsy	0.91	0.95	0.93	2608
Tumor	0.96	0.94	0.95	2570
Parkinsons	0.95	0.95	0.95	2578
macro avg	0.92	0.92	0.92	12580
weighted avg	0.92	0.92	0.92	12580

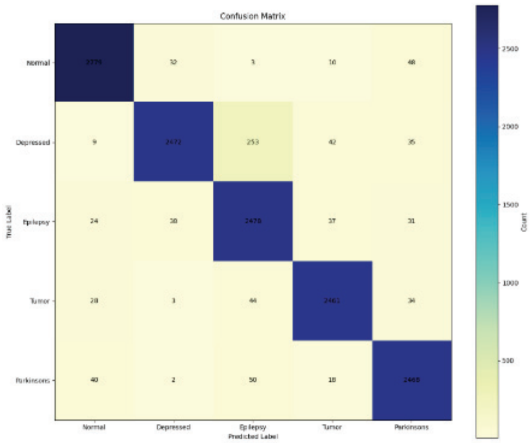

Fig. 9. EEG Ensembled Validation Confusion Matrix

G. *Final Decision Model – Transfer Learning (Ensembled + VGG19) - Results*

For the purpose of our work and comprehensive research aimed at neurology healthcare development, a Final Decision Model based on Transfer Learning approach was created. This model utilizes a proven VGG19 CNN architecture and combines it with ensemble learning methods. As a result as described in figure 11, I obtained a model which is able to diagnose the issue with a accuracy of 82.51%. Therefore, this approach can be used to develop better diagnosis methods and improve the ability to treat patients with neurological health illnesses.

TABLE VII. FINAL DECISION MODEL VALIDATION REPORT

Final Decision Model (Transfer Learning				
Class	**precision**	**recall**	**f1-score**	**support**
Normal	0.88	0.87	0.85	2470
Epilepsy	0.88	0.85	0.86	1896
Depressed	0.90	0.88	0.89	3248
Tumor	0.86	0.93	0.89	2734
Parkinsons	0.93	0.90	0.91	3177
macro avg	0.89	0.88	0.89	13525
weighted avg	0.89	0.88	0.89	13525

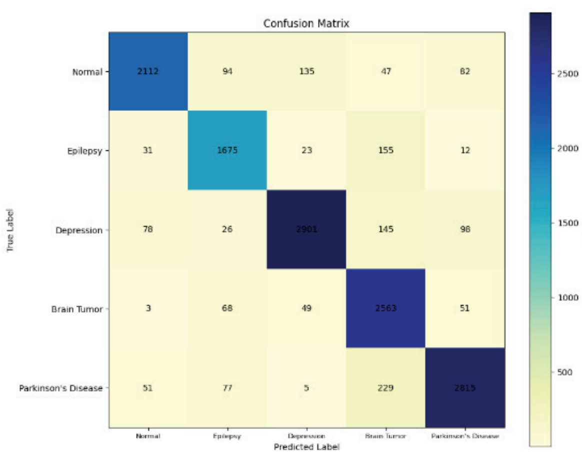

Fig. 10. Final Decision Model Validation Confusion Matrix

VGG19 showed a great outcome of 86.28% accuracy of emotional recognition, making it good for the recognition of facial expressions. The Results of Random Forest Classifier were quite high; they composed 94.48% of depression sensitivity and 90.22 of epilepsy sensitivity respectively. In addition, the result of both random forest and gradient boosting classifier indicated that they were correct in 92.12% of brain tumors' recognition and in 90.52% Parkinson's disease recognition. With the resulting accuracy of 91.83%. The combination of transfer learning, ensembled models, and VGG19 played a significant role in the final decision-making to attain an 82.51% accuracy. This suggests that pre-trained models can be used to improve classification outcomes in neurological diseases.

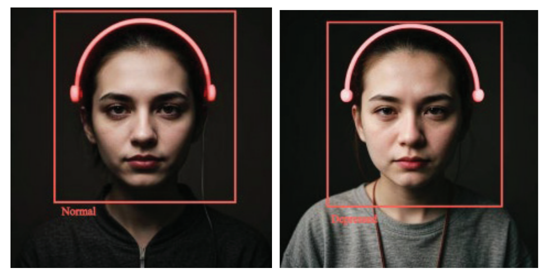

Fig. 11. Simulation results

TABLE VIII. COMPARISON OF DIFFERENT MODELS

Architecture	*Database*	*Accuracies (%)*	
		Test Accuracy	*Validation Accuracy*
VGG19	Facial Recognition - Images	86.37	86.28
Random Forest Classifier	Depression - EEG	95.01	94.44
Random Forest Classifier	Epilepsy – EEG	90.89	90.22
Random Forest Classifier	Brain Tumors – EEG	93.56	92.12
Gradient Boosting Classifier	Parkinson's Disesae - EEG	91.68	90.52
Average Ensembling	Ensembled EEG (All EEG Data)	92.41	91.83
Transfer Learning (with Ensembled)	Facial Images + EEG	83.10	82.51

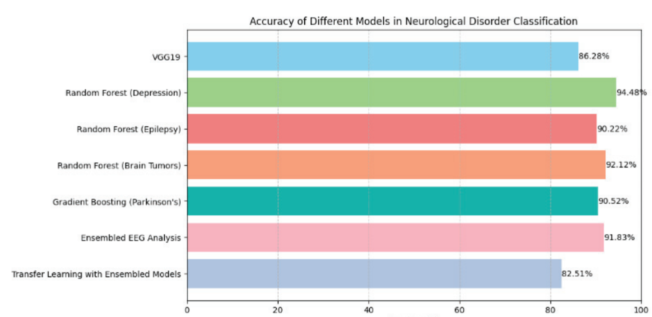

Fig. 12. Analogy of Architectures in our Model

V. Conclusion

Overall, we carefully compared different models and methods with each other and found specific features where each tool is the best. In particular, VGG19 was an outstanding facial emotion recognition tool, and the Random Forest Classifier was the best classifier for depression, epilepsy, and other diseases. The Random Forest and Gradient Boosting Classifiers were both accurate for classifying brain tumor cases and Parkinson's disease. As for the Ensembling models, metrics also confirmed the advantages of combining models for predicting conditions. Another finding is that the integration of transfer learning into our ensemble models and VGG19 produced great results, a notable increase in classification accuracy. Thus, our study shows that while a versatile approach to the problem is vital, the advances in machine learning may show us the true ways of diagnosing and managing neurological disorders. It means that further learning and research in the crossover between machine learning and healthcare can provide ample opportunities for the future of healthcare and allow people to approach diagnosis, management, and treatment in a new, more patient-centered, way. The future scope of this research has the potential to advance by investigating the capabilities of real-time monitoring and the potential of wearable technologies to improve early detection and personalized therapy [19-22].

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