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# Efficient multi-modal fusion framework with advanced AI-driven approaches for automated Parkinson's disease detection

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ABSTRACT

Parkinson's Disease is a neurological disorder, characterized by gradual loss of dopaminergic neurons in the substantia nigra resulting in: tremors, muscle rigidity, bradykinesia and postural instability. Other symptoms which involve other parts of the body and organs are as follows: loss of smell, difficulty to sleep, and changes in cognition. Being a neurodegenerative disorder, it becomes important to detect the disease in early manner. Different researchers across all over the world are trying to develop such techniques that can be helpful for disease detection process. Manually detection process based on the medical images is complex and time consuming where accuracy and reliability is also questionable. Here, deep learning came to the picture to make the process automatic and reliable where deep neural network-based models are being used to classify different diseases quite accurately and efficiently. Utilizing the potentiality of Artificial Intelligence (AI), a novel work on Parkinson's disease diagnosis has been performed with comprehensive personalized management strategies. Here in this work, AI-powered detection frameworks have been designed for Parkinson's disease classification. Seven Machine Learning models (Logistic Regression, K-Nearest Neighbors, Perceptron, Support Vector Machine, XGBoost, Decision Tree and Random Forest) and five Deep Learning Models (ResNet101, VGG19, Xception, Inception and EfficientNet) were trained and best models have been selected based on the performance analysis. Feature fusion technique with modified classification layers with hyperparameter tuning ensures optimized and remarkable output. LR and VGG19 have been selected where accuracies of 95.74 % for EEG data with LR model, 96.78 % for MRI image-based classification and 97.7 % for spiral and wave-based drawings with proposed fusion VGG19 model.

## 1. Introduction

Parkinson's disease (PD) is a progressive, neurodegenerative disorder that preferentially impacts movement and can initially manifest as tremors, rigidity or stiffness, slowing of movement, and postural instability [1,2]. These motor symptoms are a result of the absence of dopaminergic neurons in the brain, and dopamine is important in the regulation of movements [3,4]. Essentially, as PD progresses, these symptoms become magnified and significantly affect the patient's Quality of Life (QoL) and level of autonomy [5]. Early detection of the disease slows its progression and improves the prognosis; however, early diagnosis may pose challenges due to the ambiguous nature of PD's symptoms, which can mimic those of other neurodegenerative diseases [6]. Advancements in artificial intelligence, specifically in machine learning (ML) and deep learning (DL), are opening up new methods for identifying and differentiating PD through drawings [7,8]. These drawings can intrinsically identify motor control as a characteristic of PD [9,10]. Both ML and DL models have demonstrated impressive results in analyzing and recognizing PD patterns from patient drawings [10,11]. Starting from the simplest levels, we have models like the Perceptron and logistic regression that enable the separation between PD and other diseases [12,13]. Algorithms such as decision trees and random forests consider more than one feature at a time while making classification determinations, and the K-Nearest Neighbors (KNN)

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algorithm takes a closer look at drawing similarities between PD patients and other healthy individuals in order to determine the type of case in question [14,15]. Another example is the support vector machine (SVM), which uses the complex relationship between the features to prescribe significant differences in PD-specific patterns [16,17]. Growing from previous ML technologies and methods, new DL technologies allow models to work in higher dimensions of data required by the image analysis. Several models are used in this study, including convolutional neural networks (CNNs) made up of ResNet101, VGG19, Xception, and Inception [18]. These have shown to be very good at image classification tasks, especially when it comes to finding subtle features in drawings by people with PD. ResNet101's design addresses issues like the vanishing gradient problem, while VGG19 offers a relatively simple but deep network for image processing [19]. By optimizing convolution layers, architectures like Xception and Inception make parameters more accurate and efficient [20]. EfficientNet, on the other hand, scales depth, width, and resolution for better performance with less computing power [18]. Therefore, each model offers unique advantages in enhancing the ability to detect the earliest and novel signs of PD [21].

As shown in Fig. 1, pathophysiology of PD includes the details such as conversion of alpha synuclein into fibril and the formation of Lewy bodies. Parkin 1 (PARK1), Parkin 2 (PARK2) and Parkin 3 (PARK3) are the genes associated with the condition that causes the alpha synuclein to misfold and contribute towards the formation of Lewy bodies in the brain which then causes neurodegeneration. This process also had an effect of causing a drastic decrease in dopamine levels. Furthermore, PD detection and classification include the assessment of spiral drawings, imaging, EEG signals, and waves obtained from patients with PD, where DL and ML techniques are applied.

PD currently impacts over 6 million populations globally [22]. The illness affects nearly 1 million people in the United States, with approximately 60,000 new cases reported annually [23,24]. Approximately 1 % of individuals over 60 years old, and 4 % of those over 80 years old, suffers from PD [25]. Also, PD occurs nearly 1.5 times more frequently in males than in females [26,27]. These trends demonstrate the need for inexpensive but accurate diagnostic tools that can inexpensively help in the diagnosis and prognosis of PD. By comparing the data obtained from drawing tests of PD patients using ML with the data obtained from DL methods, researchers are currently developing non-invasive diagnostic tools that could potentially be available in the near future. Even though there have been recent improvements in deep learning methods, using more traditional ML methods along with more advanced DLs is still the best way to find and diagnose PD earlier and more accurately. Furthermore, stimulation techniques such as deep brain stimulation (DBS) serve as additional forms of treatment for a more advanced form of PD [28]. Similar to a pacemaker, DBS involves implanting electrodes in the part of the brain responsible for movement analysis. DBS works by using electrical signals to decrease symptoms of the disease—including tremors and rigidity—when medications are

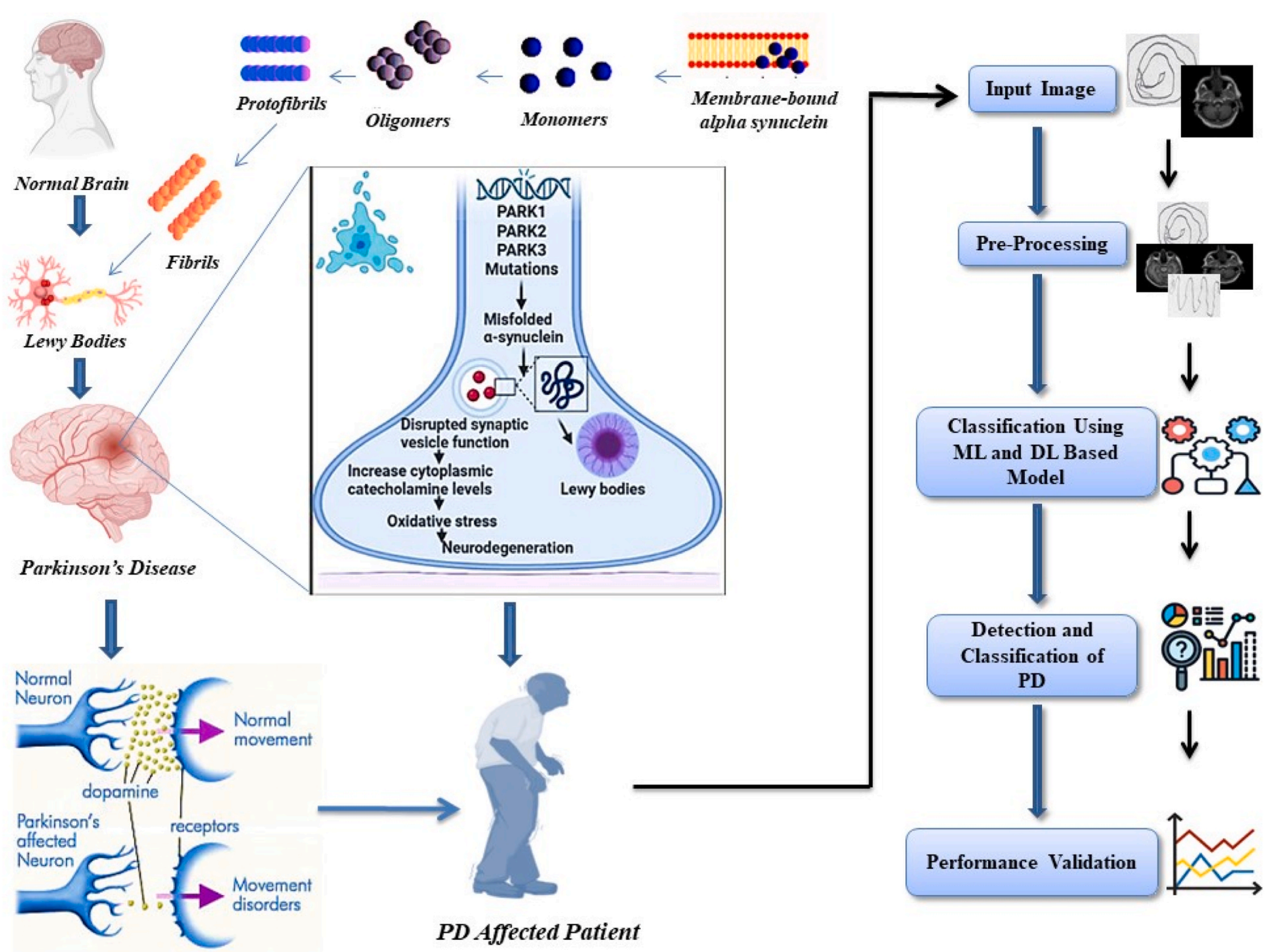



**Fig. 1.** Pathophysiology of PD and detection and classification of affected patients.

ineffective [29]. TMS extends magnetic pulses through the skull to the brain to stimulate targeted areas, while tDCS also uses currents in a similar manner [30,31]. Although these methods have the potential to relieve symptoms, they are currently considered experimental. On the other hand, physiotherapy is part of comprehensive PD management, focusing on mobility, muscle strength, balance, and falls [32]. Physiotherapy employs various approaches such as weightlifting, specific walking and balancing movements, and flexibility exercises to combat stiffness and promote proper body posture [33].

In Fig. 2, the PD symptoms shown are dementia, tremor, bradykinesia, postural instability, muscle rigidity, and loss of smell, and all of them depict the complexity of PD. Furthermore, it describe the developmental process of PD in five stages; Stage 1 involves early manifestation of symptoms and is usually unilateral; Stage 2 refers to mildly impaired and still unilateral; and Stage 3 involved moderately impaired and at this time, the symptoms could be bilateral; Stage 4 identified as moderately to severely impaired, with the patient having postural instability; and the final Stage 5 involves severely impaired patients who cannot stand or walk and This progression shows how PD affects the decrement of both motor and non-motor functions in patients.

Clinically oriented treatments such as LSVT BIG utilize large and excessive reps for every movement to address PD's hallmark, bradykinesia [34]. Speech and language therapy, typically a form of PD physiotherapy, uses techniques such as LSVT LOUD to amplify the volume of an individual's voice, as individuals with PD often have weak speaking muscles [35]. Combined, they present a myriad of general management strategies for mitigating the effects of PD on upper limb function and functioning.

In Fig. 3, prevalence of PD across different countries is showing where it can be observed that the United States is in the second highest position. The number of affected rate is getting increased day by day where affected persons are mostly of old ages [35]. Researchers from all over the world are working relentlessly to find a solution by discovering such approach through which PD can be detected in faster and efficient way.

The proposed work introduces novel approaches where following objectives have been achieved:

- An extensive review of literature has been done through which recent developments with existing state-of-the-arts have been thoroughly studied.
- Three types of classification frameworks (EEG data-based classification, MRI image-based classification and spiral-wave drawing data based classification framework) have been trained with optimized ML models and modified fusion DL models. The proposed frameworks developed with cutting edge AI-driven approaches ensure high performance in term of rich accuracy, sensitivity, efficiency, and reliability. The use of feature fusion method applied on modified classification layers with optimal hyperparameter settings ensure maximized and impressive output.
- A systematic comparative analysis has been done to figure out the current gaps and compared the novelty of the proposed work with other existing works. The comparison demonstrates that the proposed frameworks are superior to previous approaches in accuracy, sensitivity, and reliability, as well as dealing with limitations identified in the literature.
- In addition to model development, an IoT-based integrated framework is proposed as a novel extension pathway for clinical application to achieve continuous monitoring, real-time analysis and remote patient management thus closing the gap between the computational research and the actual implementation of healthcare.

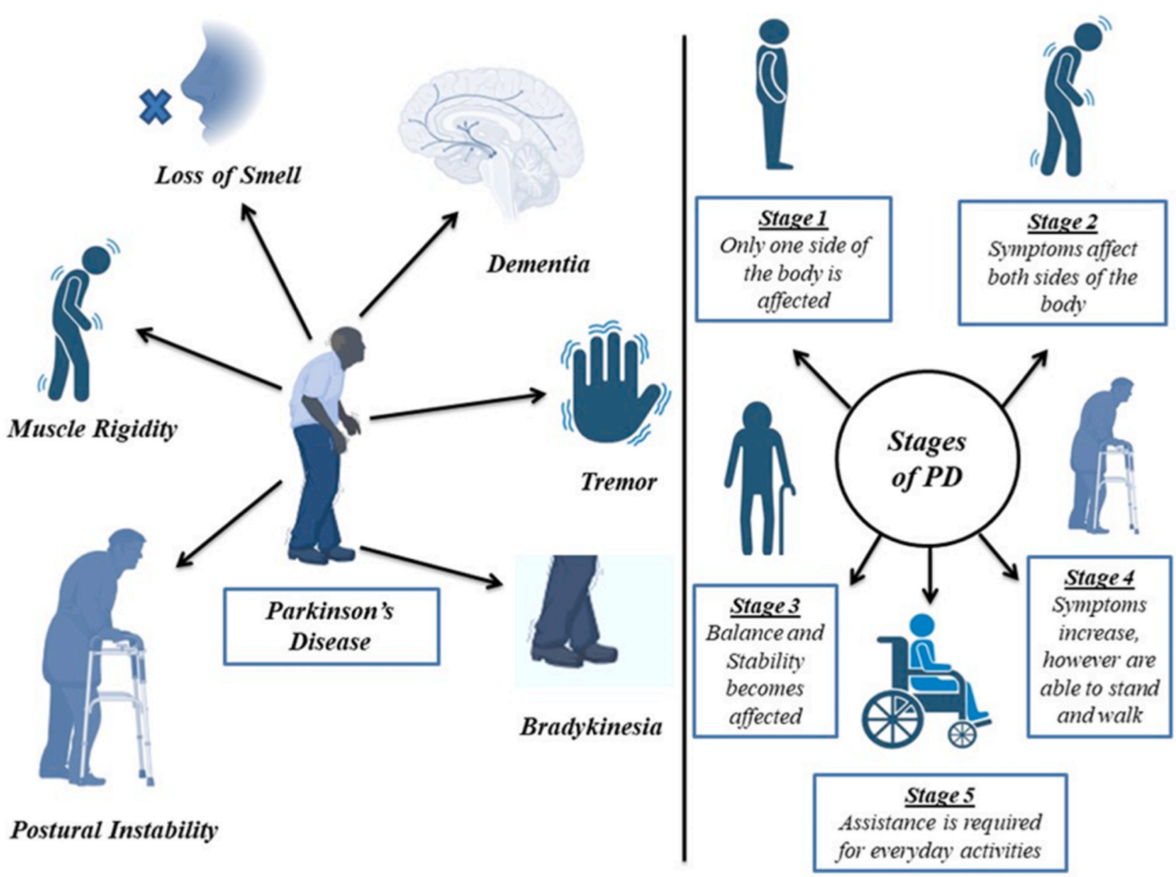



**Fig. 2.** Symptoms and progression stages of PD

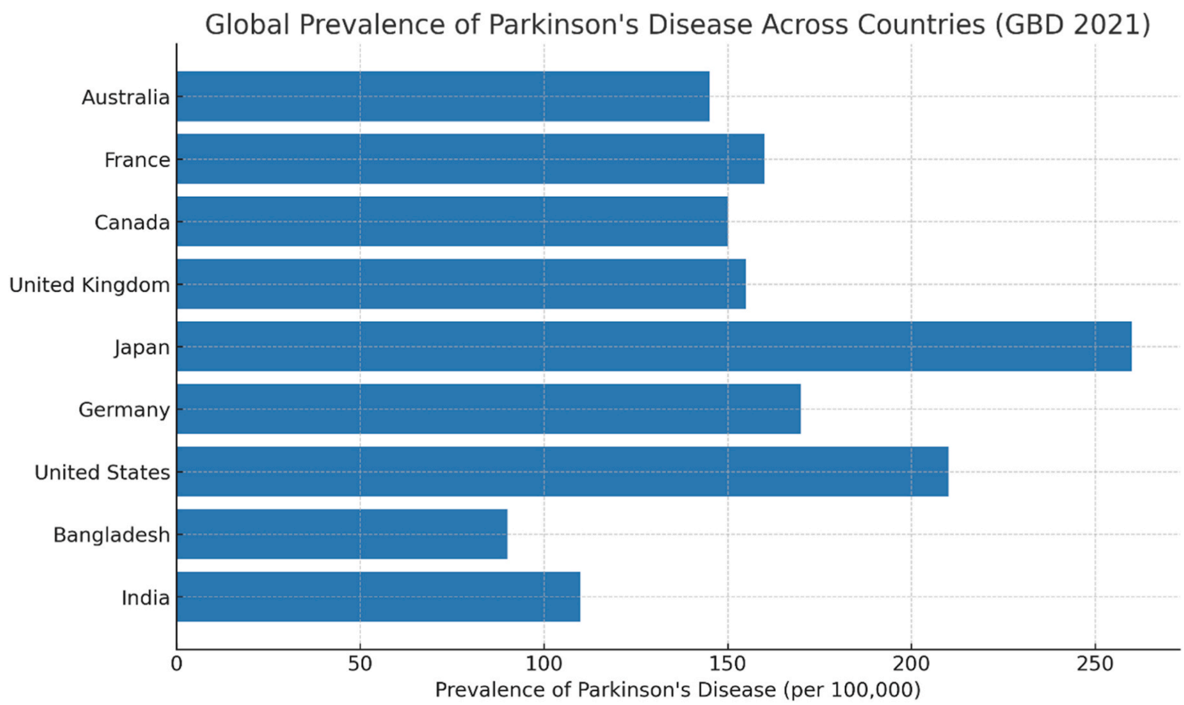



**Fig. 3.** Global prevalence of PD across countries (GBD 2021) [36].

In Sec 2, review of literature has been done where recent works have been analyzed to find out gaps and limitations. After doing the literature study, observation got matured that what has been done till now on this particular field and what can be done in future. In Sec 3, proposed methodology has been presented where dataset description, model selection, model building including architectural developments and functionalities have been discussed. Sec 4 deals with the results and discussion where qualitative and quantitative results have been analyzed, presented, and discussed thoroughly. A comparative analysis has also done to justify the strength and novelty of the proposed work with existing state-of-the-art works. . Conclusion of the work has been drawn in Sec 5 where summarization of the outcomes with related future works have been covered. Finally, a list of references which were used to support the work have been properly given.

## 2. Literature review

Recent advancements in smart detection systems for PD have applied a few innovative solutions for early diagnosis and monitoring progress of the disease. Quan et al. (2021) analyze both dynamic and fixed parameters by employing the Bidirectional Long Short-Term Memory (LSTM) model. They demonstrate that the different patterns of articulation exist in Parkinson's patients as compared to controls. This is helpful before the disease reaches the next stage and other management strategies become difficult [37]. In order to emphasize the importance of early detection, Qiu et al. (2024) developed an EEG analysis that incorporated MCPNet, a first-order prototype network that effectively reduces noise impact and boasted 97.87 % in-set accuracy and 94.87 % out-of-set accuracy [38]. In the same context, Zhang et al. (2022) developed EEG based biomarkers for functional brain networks. This made it much easier to diagnose early PD patients in the clinic [39].

Wearable technology also has great importance; Tong et al. (2021) came up with a CNN-based model that predicts hand tremors from wrist acceleration data, distinguishing PD-related tremors [40]. This line of research was further extended by Devarajan et al. (2023), who improved the diagnostic accuracy using ML ensemble models and nonclinical voice data [41]. Talitckii et al. (2021) presented a technique that combines ML with wearable sensors, which has a distinguishing accuracy of 0.9 AUC for 15 diagnostic functions, which can be very useful in clinical practice [42]. In the same way, Shcherbak et al. (2023) used wearable sensors in creating exercise sets suited for early diagnosis of PD; this significantly boosts the possibility of interventions at the earliest sign of the disease [43]. Technologically, Shi et al. (2022) proposed a sensor-based monitoring system for the identification of gait freezing [44], while Lin et al. (2022) took advantage of IMU-derived motion data for an accurate diagnosis of early PD [45]. He et al. (2024) investigated the use of digital biomarkers that could be recorded while walking on a smartphone. They found that the exercise had a low rate of false negatives for the first suspect [46].

On the other hand, Reddy et al. (2023) came up with new ways to use exemplar-based sparse representation to improve the rate of classification for PD [47]. Khan et al. (2021) did a systematic review of 147 papers and, like the preceding study, focused on the use of ML and DL to diagnose PD and other brain illnesses. According to them, AI could be helpful in clinical diagnosis, though they also mentioned some issues that could prevent the progress [48]. Hossain et al. (2023) made a significant contribution by integrating a cyber-physical deep meta-learning framework, enriched with contrastive learning and featuring a CNN encoder, to enhance diagnostic capabilities with minimal data [49]. Zhang et al. (2023) looked into how GNN could be used with MRI data. They also noted that a multiple-layer GNN approach was less prone to over-fitting and easier to construct compared to the other models they proposed [50]. Taken together, there are only published works on handwriting analysis particularly applied to early disease detection by the works of Allebawi et al. (2024), where the objective is to identify the disease through better and improved data augmentation as well as DL architectures [51].

In their comprehensive review of the literature, Mughal et al. (2022) focus on the positive effects of wearable technology in PD and point out that there may not be enough research findings on how to track non-motor symptoms [52]. Khare et al. (2021) have also discussed an EEG signal analysis model that employed a convolutional neural network for precise PD prediction [53]. To fill these gaps, Allebawi et al. (2023) contributed a new Arabic handwriting dataset [54], which could facilitate both early PD detection and the monitoring of its symptoms during both ‘on’ and ‘off’ phases and subsequent rehabilitation. Instead, Xu et al. (2022) aimed to classify PD from healthy controls using resting-state fMRI data and a more recent brain network approach; they considered key connectivity hubs in the basal ganglia and cerebellum for PD differentiation [55].

Moreover, Salman et al. (2023) illustrated the usefulness of the vocal analysis in automated diagnosis of PD utilizing a CNN-LSTM model with 97 % accuracy and, therefore, speaking in favor of the further utilization of the speech-based diagnostics for PD [56]. Kumar et al. (2023) analyzed the relationship of hospitals and PD to heart diseases through the comparative quantitative study using the Extreme Gradient Boosting

**Table 1**
Overview of related studies.

| Author(s) | Model Used | Dataset | Total Images | Methodology | Accuracy | Focus Area | Limitations |
|---|---|---|---|---|---|---|---|
| Cui et al. (2024) [73] | MSHANet (Multiscale-Hybrid Attention Network) | SV_3 and MV_3 Augmented Dataset | 6120 images | Utilized CNN with hybrid attention blocks, achieving high accuracy with multiscale convolution | 94.11 % | MRI-based PD detection | Computationally intensive; limited to specific brain regions |
| Chen et al. (2023) [74] | CNN-based model for gait analysis | Wearable IMU dataset | 1832 Windows | CNN optimized for detecting gait-related PD features using continuous wavelet transforms | 98 % | Gait biometrics in PD | Requires multiple sensors; costly for extensive data collection |
| Palakayala et al. (2024) [75] | LUNet (LeNet + U-Net hybrid) | PPMI Database | 500 (Real) and 2500 (Augmented) MRI images | Applied U-Net and LeNet components to MRI data for highly accurate PD detection | 99.58 % | MRI-based PD identification | Model is complex and resource-intensive |
| Suuronen et al. (2023) [76] | Minimal EEG setup | Resting-state EEG dataset | 309 EEG samples | Used five optimized EEG electrodes for PD detection to minimize setup costs | 76 % | Cost-effective EEG-based diagnostics | Lower accuracy than full EEG setups |
| Abdullah et al. (2023) [77] | TL, KNN, Genetic Algorithm | HandPD dataset | 594 Images | Used genetic algorithms for feature selection in handwriting-based PD detection | >95 % | Handwriting biometrics in PD detection | Limited to specific handwriting tasks |
| Demir et al. (2021) [78] | LSTM with image-mapped features | Custom voice dataset | 756 samples | LSTM for end-to-end feature extraction and classification for PD voice analysis | 94.27 % | Voice-based end-to-end PD diagnosis | Requires computationally intensive data preprocessing |
| Naz et al. (2023) [79] | Deep CNN (AlexNet, GoogLeNet, VGG16, VGG19, ResNet50 and ResNet101) with data fusion | HandPD, NewHandPD and drawing dataset | 736 images, 594 images and 204 images of drawings | Combined multiple CNNs for feature fusion, achieving higher accuracy than single CNNs | 99.35 % | Handwriting-based PD diagnostics | Requires computationally intensive fusion processing |
| Shuqair et al. (2024) [80] | RL + LSTM | PD1 and PD2 Dataset | 12 Subjects (PD1) and 7 Subjects (PD2) recordings | RL to monitor medication states in PD, improving detection of ON/OFF states | 82.94 % F1 (PD1) 76.67 F1 (PD2) | Personalized therapy monitoring | Real-world validation needed; may have bias with controlled data |
| Dong et al. (2023) [81] | Static-Dynamic temporal networks | Gait data from wearable sensors (Three Independent Research Groups) | 166 gait sequences, 64,468 (Segments of given subject) | Combines static/ dynamic pathways with CNN to analyze nuanced gait patterns | 96.7 % (Diagnosis) 92.3 % (Severity Prediction) | Gait biometrics in PD | May have limited sensitivity to early PD stages |
| Li et al. (2023) [82] | CNN-RNN | UNM and UI datasets | 82 PD Patients | Hybrid DL with CNN for feature extraction and RNN for temporal dependencies | 95.23 % | EEG-based PD detection | Limited to resting-state EEG; requires larger datasets |
| Igene et al. (2023) [83] | ML | PD-BioStampRC21 (accelerometer data) | 17 PD and 17 Healthy Patients | Analyzed daily movement data from accelerometers, focusing on symptoms missed outside clinical settings | 92.6 %–94.4 % | Wearable sensor-based PD diagnosis | Small sample size; limited in-capture data granularity |
| Chiu et al. (2024) [84] | Facial feature analysis model | Custom static image dataset | 30 PD Patients and 30 Healthy Control Subject | Facial symmetry, eye aspect ratio, and muscle tension analysis to identify PD patients | Face Symmetry (98.3 %) Eye Aspect Ratio | Facial expression analysis for PD | Sensitive to image quality; needs environmental controls |
| Shreya et al. (2024) [85] | Boosting algorithms | HandPD Dataset | 92 Individuals | Anomaly detection in drawing patterns, leveraging statistical analysis and ML algorithms | AdaBoost (94 %) XGBoost (97 %) | Drawing-based PD diagnostics | Data quality variability; model requires extensive validation |
| Gupta et al. (2023) [86] | ML (SVM, RandomForest, KNN, XGB) | Custom speech dataset | 195 Voice Recordings | Early-stage vocal biomarker analysis for PD detection using ML | 92.30 % | Voice-based PD detection | Accuracy depends on recording length, quality, and accent variations |
| Smolik et al. (2024) [87] | Wav2Vec 2.0 (transformer-based) | Italian speech data | 59 Subjects | Transformer model applied to cross-language speech intelligibility for PD analysis | 58 % | Speech intelligibility as PD indicator | Limited support for non-native languages |

algorithm to predict the conditions of the PD patient with heart diseases [57]. Ziyadh et al. (2024) suggested a mixed IVHA and handwriting analysis model that employed ML and DL algorithms, which depicted an optimistic result in terms of reachability of diagnostic accuracy [58]. Gaba et al. (2024) showed how several similar ML techniques aim to predict PD progression in an assortment of papers, which include limitations and potential development for more useful versions of the model [59]. Hussain et al. (2022) performed vocal analysis, which diagnosed the PD onset with 93 % accuracy; the authors concluded that speech impairment is one of the most significant early signs of the disease [60].

Delgado et al. (2023) proposed a preliminary radar-based gait biometrics for PD that can provide a new direction for gait biometrics with the aid of an asymmetrical baseline in early detection of the disease [61]. In applying a pipeline based on speech and audio data, Tesfai et al. (2023) achieved staggering 99.82 % accuracy of diagnosing PD [62]. Wachiracharownong et al. (2024) suggested that Archimedean spiral drawings could be used for the assessment of PD and got 82 % accuracy at the same time, making early diagnosis affordable [63]. Nalini et al. (2023) presented a ML model of speech carriage features, including pitch, jitter, and shimmer, all of which could be effectively used to differentiate between HD patients and normal persons [64]. Naanoue et al. (2023) analyzed the features of the speech using the LSTM model and observed a 93 % accuracy ratio; they also recommended the use of the signal in the early diagnosis of PD [65].

In their separate study, Sandhiya et al. (2022) employed increased imaginative and prescient like spiral and wave-like drawings along the side of gait and stumbled upon enhancements on utilization of RF Classifiers of prediction PD Early that are tremendously important [66]. Kumar et al. (2023) used YAMNet to post-radiolabeled speech signals for detecting early PD with 82 % accuracy [67]. In the PD detection, Khan et al. (2023) introduced a convolution-based network incorporating attention mechanisms, achieving an overall accuracy of 98 % and other rigorous evaluation measures, including a precision of 0.99 [68]. In the study conducted by Chang et al. (2022), the IMU was used as the parameter in evaluating PD motor symptoms, and their system efficiency in identifying the various motor symptoms was 87 %, 90 %, and 95 %, respectively [69]. Gupta et al. (2023) also focused on identification and analysis of protein and peptide biomarkers for early diagnosis of PD from control patients and reached promising predictive classifiers employing RF Modes [70].

Furthermore, Burri et al. (2023) described that PD has the possibilities of the new quantum computational technology for the diagnosis and treatment of the disease and anticipated that it enhances the diagnostic accuracy by handling vast quantitative genetic and medical data, although there are some limitations and the use of quantum computing has some ethical issues [71]. Finally, Madhavi et al. (2023) suggest using the ULM in order to analyze hand drawings for PD detection and claim that the recognition accuracy, precision, and recall are noticeably high, pointing at this method as one of the low-cost and noninvasive early diagnosis techniques [72]. In sum, these works must be viewed as a methodological synthesis of the multi-dimensional model for the enhancement of the PD diagnostic and therapeutic approaches by means of the technology that will remain promising for further investigations and practical applications. A summary of the related existing works are presented in Table 1.

## 3. Proposed methodology

### 3.1. Dataset description

To train ML and DL models, data instances are required. ML models work well with less amount of data, where it requires huge amount of data to train DL models. In healthcare applications, reliability is a big concern. To build a reliable system, data from authentic and benchmark resources are required. Three different datasets have been used to develop the proposed frameworks. To implement the proposed ML-based framework, the Parkinson Diseases EEG Dataset was utilized [88]. The dataset is publicly available on Kaggle (https://www.kaggle.com/datasets/s3programmer/parkison-diseases-eeg-dataset), that comes with EEG (electroencephalography) signal data collected from both healthy subjects and Parkinson's-affected individuals. All the data are derived from EEG recording, and each record contains preprocessed EEG signal features extracted from multiple brain regions. The features are represented with numerical values. The dataset offers 756 samples and 755 EEG-based feature columns, that quantify the statistical and frequency-domain characteristics of the EEG signals. This dataset has been selected because EEG signals effectively capture neural activity changes that put significant impact to track Parkinson's disease progression. The second dataset that has been used for MRI brain image classification to detect PD is ''NTUA_Parkinson_MRI'' dataset [89]. The dataset is designed with two classes having two separate folders for Normal and Parkinson's patients. Each folder consists of MRI brain images for different subjects.

Fig. 4 shows the dataset samples in form of MRI images of brain where two categories of images are there. The third dataset is 'Parkinson's Drawings' dataset that comes with spiral and wave drawings of healthy and Parkinson's patients [90].

The dataset is developed with processed images of spiral and wave drawing having different characteristics like pen pressure, speed, stroke, thickness etc. The dataset is split between two folders for training and testing purposes. Fig. 5 shows the images sample of spiral and wave drawings of PD and healthy patients. These three datasets have been mentioned as DS1, DS2 and D3 to be used and explained in the rest of the paper for better understanding.

### 3.2. Data preprocessing

To enhance the performance of the models, preprocessing is an important and necessary steps which has been done both in ML and DL-based approaches. Before doing the preprocessing, datasets need to be loaded first to access each data instance. Although the used datasets are developed with preprocessed images, further additional preprocessing can put positive effects on overall performance of the proposed framework. DS1 is consisted of numerical values where 756 EEG recording data with various measurement parameter have been given for healthy and Parkinson's patients. Almost 755 parameters are there for each recording. All the parameters are not equally important to be considered for model training, even this may create overfitting issues. In overfitting, testing error is greater than training error. Another type of error is under fitting which may be occurred for less amount of data where both training and testing error is high. To reduce overfitting, important parameters have to be selected for training and each parameter is considered as features. Out of 755 features, best 20 features have been selected to train for ML based framework.

**Train-Test Split:** In DS1, total 756 instances are there among which data has been split to 90:10 ratio where 680 instances for training data and 76 testing instances have been used to validate models. In the DS2 dataset, two separate folders have been created for healthy and affected patients.

Total 6502 MRI images have been used among which 5849 images have been used for training and 653 images for testing purpose. In DS3, two different directories are there for spiral and wave drawings. In each folder, data are given separately with 6075 and 3540 training and 650 and 429 testing images for spiral and wave drawings respectively. Fig. 6 presents the train test ratio of each dataset used in the work.

**Regularization and Normalization:** In ML, regularization technique is used to reduce errors by fitting function perfectly to the training sets. Two types of Regularization techniques are L1 and L2 regularization where L1 adds sum of absolute values and L2 adds sum of squared values of the coefficients of the models. Regularization avoids complicated models that could fit irrelevant patterns or noise in the training data, thus preventing overfitting. Rather, it encourages the utilization of

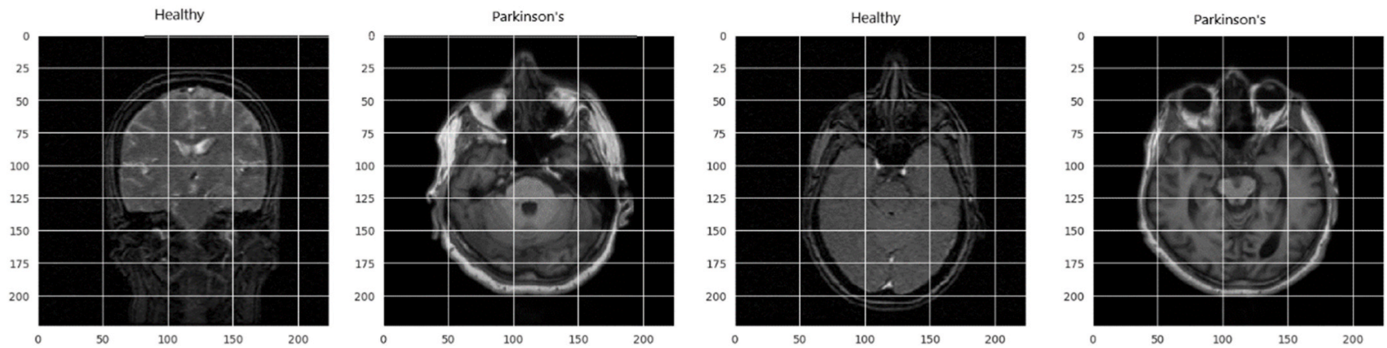



**Fig. 4.** Brain MRI images of healthy and affected patient.

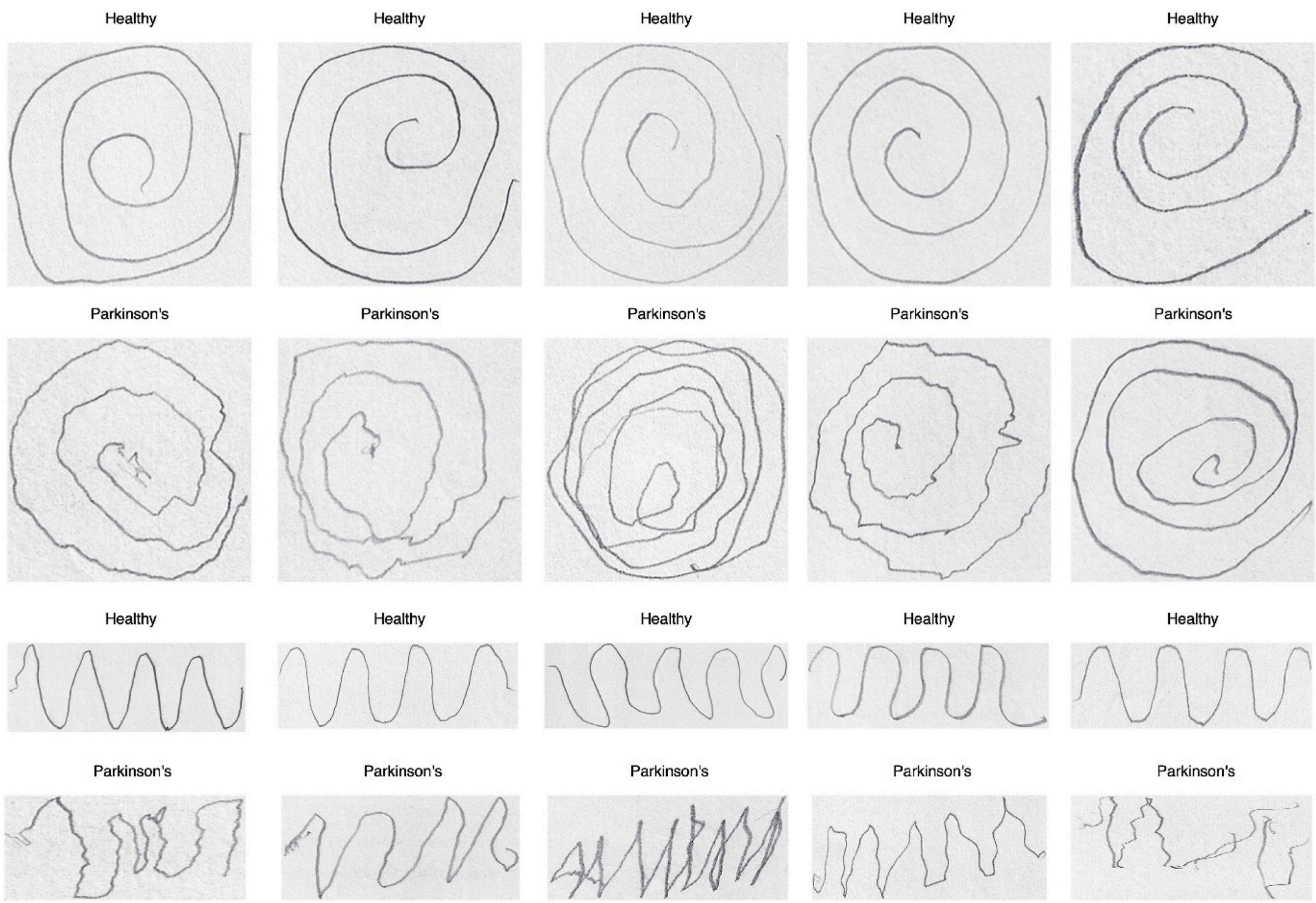



**Fig. 5.** Sample of spiral and wave data instances for health and Parkinson's patients.

more simple models that effectively preserve the underlying patterns and adapt to new data. While working with small amounts of data or high-dimensional datasets and models having numerous parameters, regularization is especially helpful.

Normalization is applied to normalize the data by transforming the values in a common scale so that all variables in the data maintain similar range without missing any information. Normalization technique plays significant role to enhance the overall performance of the system. In this work, standard scaler function has been used with DS1 dataset where features have been standardized by scaling with zero mean and unit variance.

Fig. 7 shows the correlation of features that have been used from DS1 where importance of the selected features can be identified.

The detailed information has been presented for each feature in Fig. 8 with respective kurtosis values. Kurtosis is considered as descriptive statistics that shows the dispersal of center and tail of a data distribution, and Kurtosis can be measured using the following formula that has been modified to suit our work [42]:

$$\mathrm{Krt} = \frac{\sum (x_i - m)^4}{(N \times \mathrm{Std})^4} \tag{1}$$

Here, krt: Kurtosis value
Xi: Random sample
N: number of samples
m: mean value

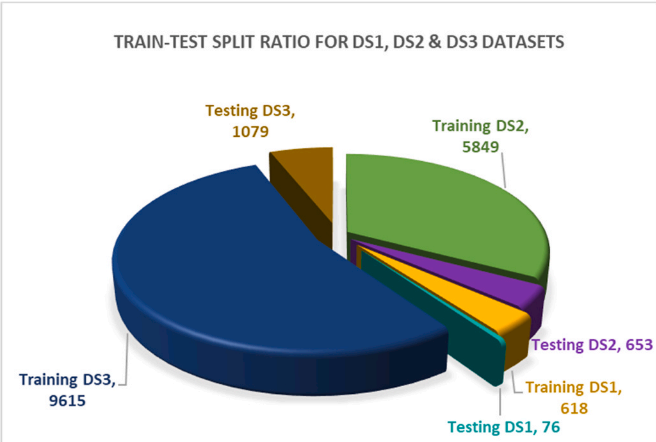



**Fig. 6.** Data distribution for training and testing.

Std: Standard deviation

Here, for each feature data, Kurtosis value has been calculated using a predefined function 'kurtosis()'.

**Denoising:** To enhance the performance of CNN models in image-based applications, image quality matters significantly. Different image denoising techniques like spatial filtering, temporal accumulation etc. and models like auto encoders are being used. Better quality of images ensures the better result from the developed framework.

**Augmentation:** Augmentation helps to enhance the overall accuracy of the system. Two types of data-synthetic and augmented data can be generated to reduce the data limitation. Synthetic data are the purest form of data that are artificially created using generation algorithm. GAN or Generative Adversarial Network is one of the most popular generation algorithms that can generate synthetic data. Augmented data are modified form of actual data using different image transformation techniques like resizing, reshaping, rescaling, rotating etc. Here in this work, an augmentation approach has been developed and followed by which instances have been increased significantly. Fig. 9 shows the steps of the proposed augmentation approach where multiple augmented data have been created. Data have been pooled first from the input directory.

Left-right rotation, flipping, zooming, color adjustment and shearing have been done and the augmented images are stored in the output directory. Initially, Datasets have less amount of instances where DL models require huge instances for better performance. After doing augmentation, instances have been increased multiple times higher. Fig. 10 is showing the augmented data status of DS3 dataset. The Nested

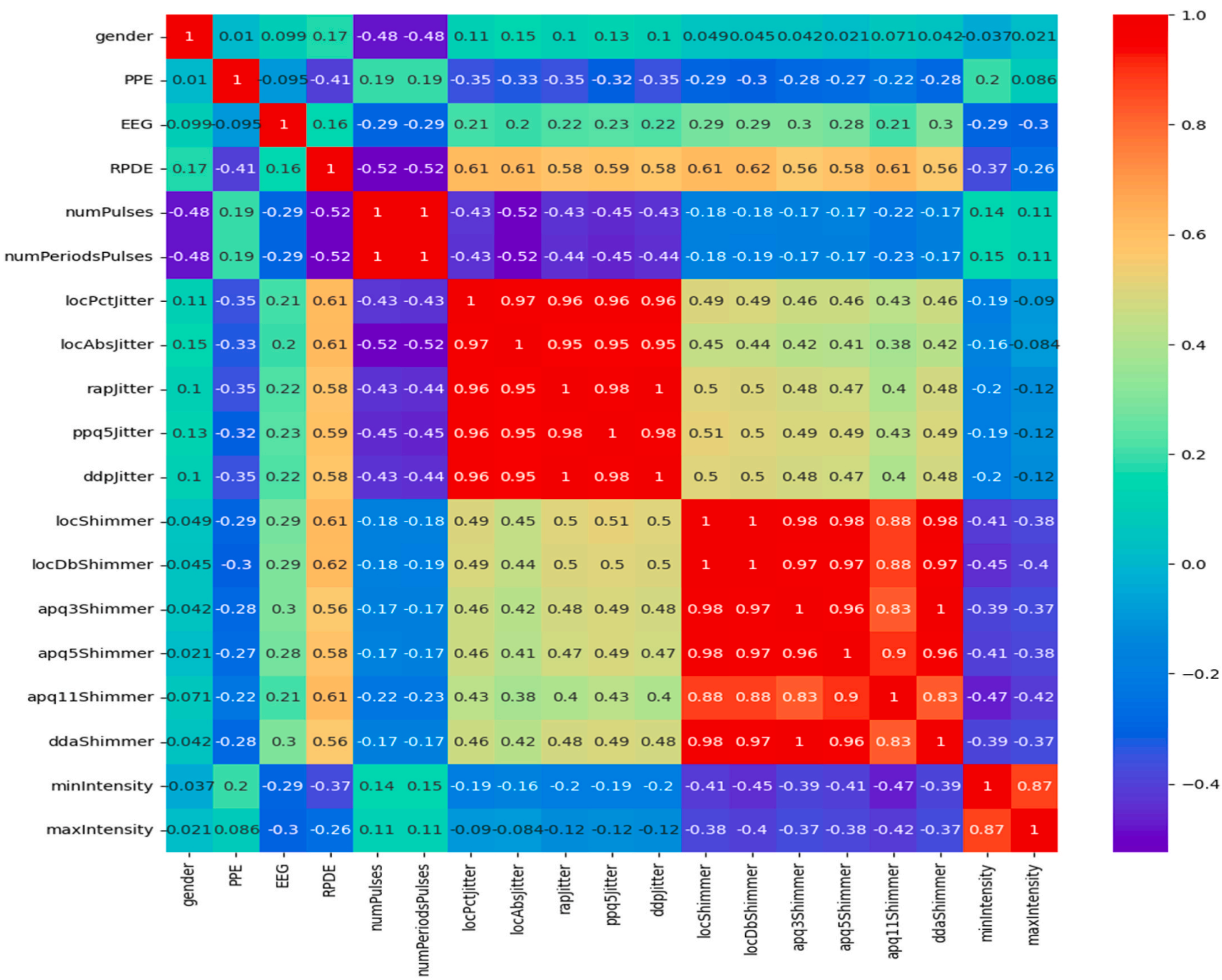



**Fig. 7.** Feature correlation heat map for DS1 dataset.

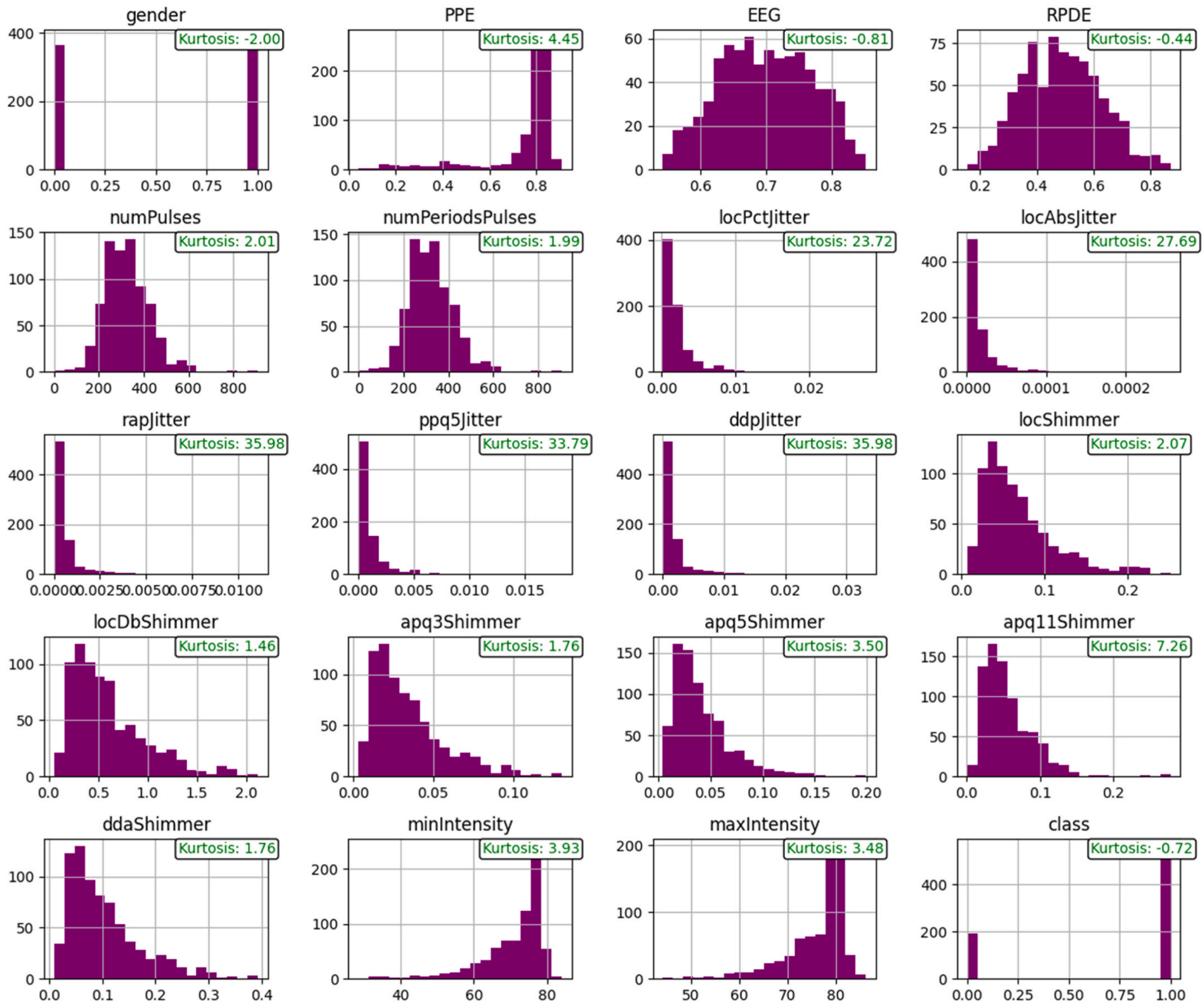



**Fig. 8.** Histogram representation of feature status with Kurtosis values.

Pie chart (a) is train-test values for spiral and wave drawings after doing augmentation. The column chart (b) is showing the comparison of the initial values and augmented values of the wave and spiral category of DS3 dataset.

### *3.3. Model training*

#### *3.3.1. ML model selection rationale*

Supervised models are based on supervised learning architecture where models are trained with input features with respective labels. Supervised models are generally used for classification and regression. Some of the models that are based on supervised learning architecture are: Logistic regression, Linear Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF) etc. In unsupervised algorithms, labeled data is not required during training which are mainly used for clustering or grouping. C-Means, K-Means are unsupervised algorithms which are popularly used for clustering applications. Proposed work is based on classification technique, so that seven ML algorithms have been used which are used for classification purposes. Seven widely recognized machine learning algorithms- Perceptron, KNN, SVM, RF, Decision tree (DT), XGBoost and LR were selected to train on DS1 dataset based on their robustness, strengths and prominent efficiency in classification tasks. Logistic Regression, is selected due to its simplicity and interpretation, LR was selected as a baseline linear model to test if the dataset can be separated linearly. SVM is chosen due to its effectiveness in processing high dimensional data and non-linear boundaries of decisions with the help of the kernel functions. KNN is a non-parametric model that is also useful in the capturing of the local patterns and it uses distance-based similarity.

DT can deal easily with both numerical and categorical features. RF is considered as an ensemble technique that reduces the problems of overfitting, and improves generalization through a combination of trees. Perceptron is one of the first neural network models that are added to investigate a linear classification as a neural perspective. XGBoost is chosen because of its high predictive ability, gradient boosting model, and the capacity to deal with interactions of various features effectively.

All the models have been trained with labeled data to perform classification. Among the seven models, LR or Logistic Regression performed better with higher accuracy. Linear regression is basically used for regression where LR is used for classification purpose. LR is supervised learning algorithm which is easy to be implemented with linearly separable dataset with generating valuable insights. LR is mainly used

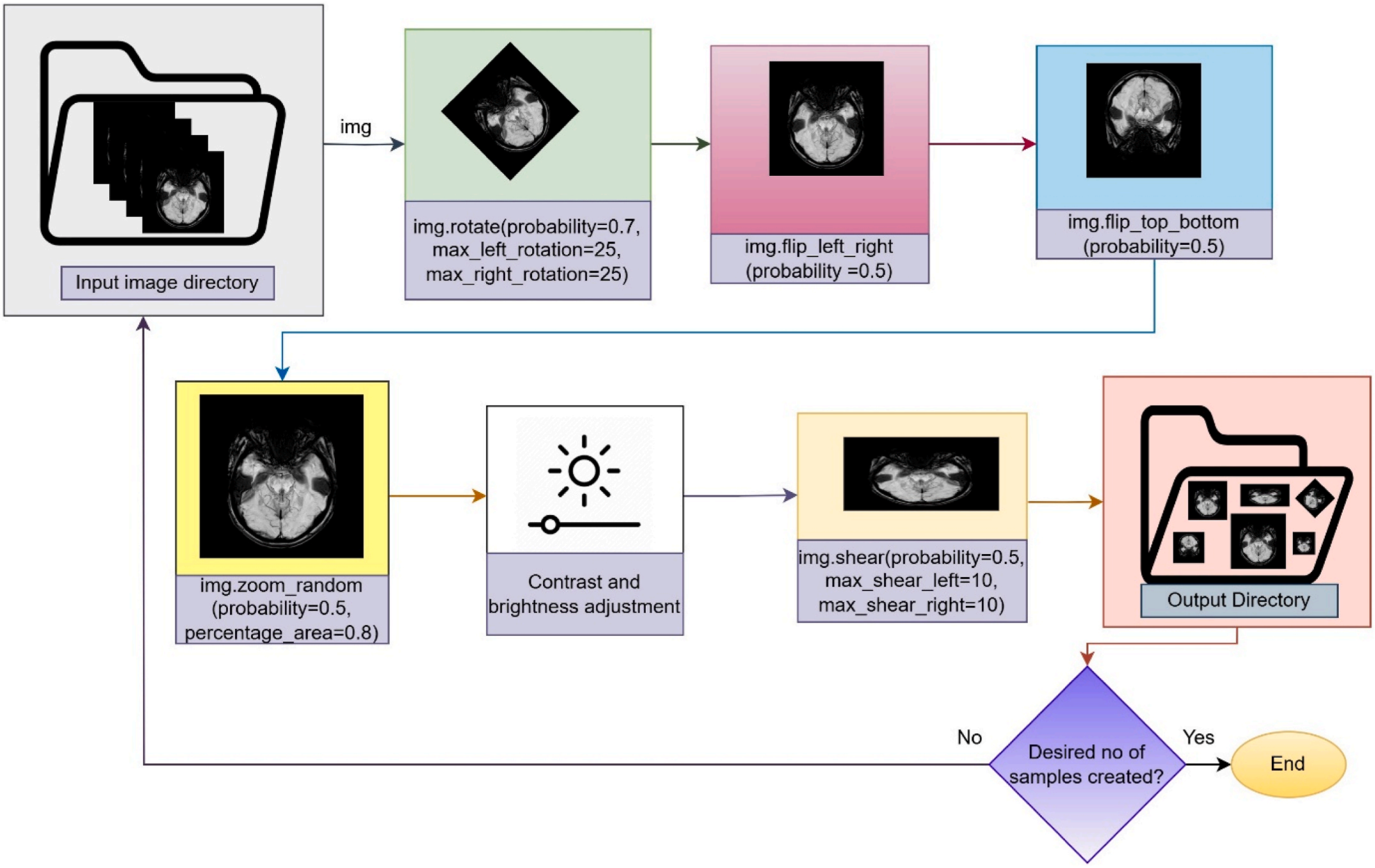



**Fig. 9.** Steps for augmented data generation approach.

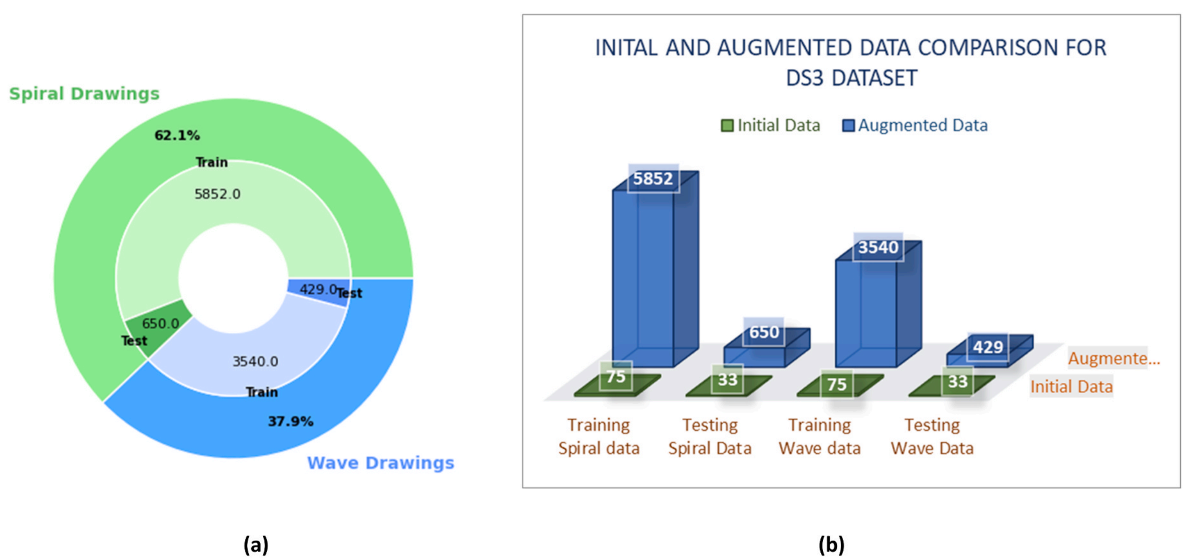



**Fig. 10.** Quantitative presentation of augmented data from DS3 dataset. **(a)** Augmented spiral and wave drawings quantity for training and testing. **(b)** Quantitative comparison between the initial and augmented values of Spiral and wave drawings.

for binary classification. Sigmoid function acts as LR activation function L(z) [64] where:

$$L(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

Z is the value to transform and e is the base of natural algorithm.

$$Y_{o/p} = \frac{1}{1 + e^{-(q+px)}} \tag{3}$$

In the place of z value, equation of line is replaced where q is intercept term and p is the coefficient of input (x) value. Y_(o/p) is the predicted value that will generate binary outcome (0 or 1) unlike linear regression. Normally, the threshold value is considered as 0.5, if the obtained value

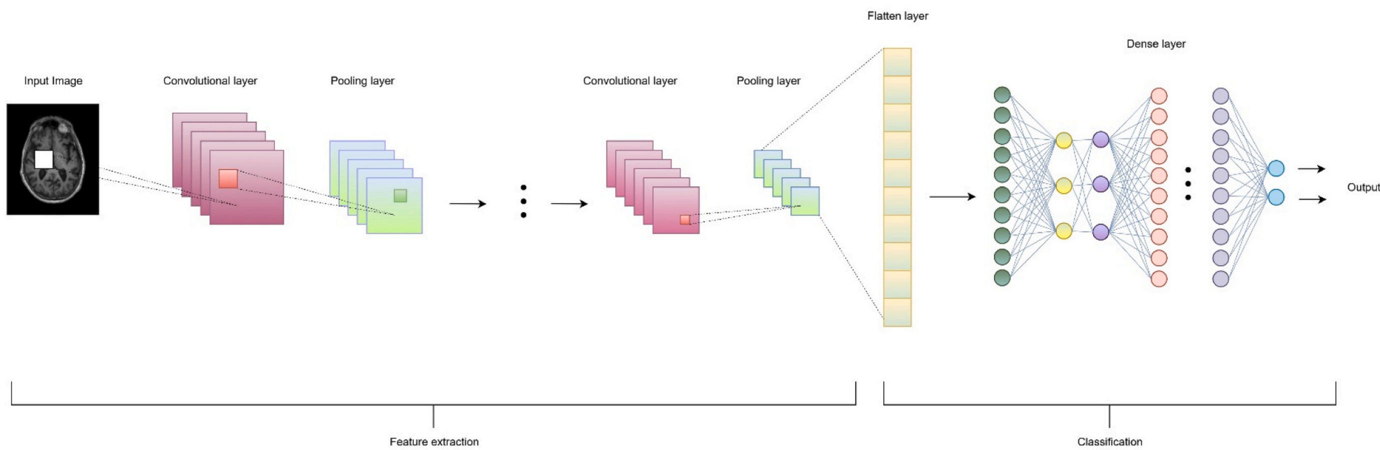



**Fig. 11.** Architecture of VGG19 model.

is less than threshold value, the predicted outcome will be 0 else it will be 1.

### *3.3.2. CNN models for classification*

Deep learning being a subset of machine learning is being applied on classification where deep neural network can perform multiple complex operations efficiently. CNN or Convolutional Neural Network is deep neural network based architectural models that is widely use on unstructured data like audio, images and videos. To classify images, different types of CNN models are being used where models are trained with images first and used for classification. ResNet, VGG, GoogleNet, AlexNet, EfficientNet, Inception, Xception, MobileNet etc. are popular models based on CNN architecture. With transfer learning technique, pre-trained models can be used where pre-built knowledge can utilized. In the proposed framework, VGG19, ResNet101, Xception, Inception and EffiecientNet have been trained. Based on the high performance in overall parameters, VGG19 has been selected where the pre-trained model is developed with feature fusion technique that offers more efficient result.

*3.3.2.1. Feature extraction and classification.* In CNN, the architecture can be divided into two parts based on the working functionalities that are feature extraction and classification. The convolutional part deals with the feature extraction and dense network park works for classification. Fig. 11 is showing a basic architecture of CNN where general steps of CNN model building are presented. Data are required to be fed into the model as input. In the figure, image classification process is presented with basic steps. Images are noting but collection of pixels or dots. Kernal works as filter that crop a portion of the group of pixels from the input image and the data to the convolutional layers. Convolutional layers extract the information. Pooling layers pool the most relevant information from the features.

Different types of pooling mechanism are there like max pool, sum pool and average pool. The extracted feature is arranged in a 1-D array which is known as flatten layer. In dense layer, each node is inter connected where activation function in the output layer triggers the final classified output.

Fig. 12 shows the architecture of VGG19 which is used in proposed framework. Here five types of convolutional layer are used with max pooling. The feature extraction part is showing the roles of each layer

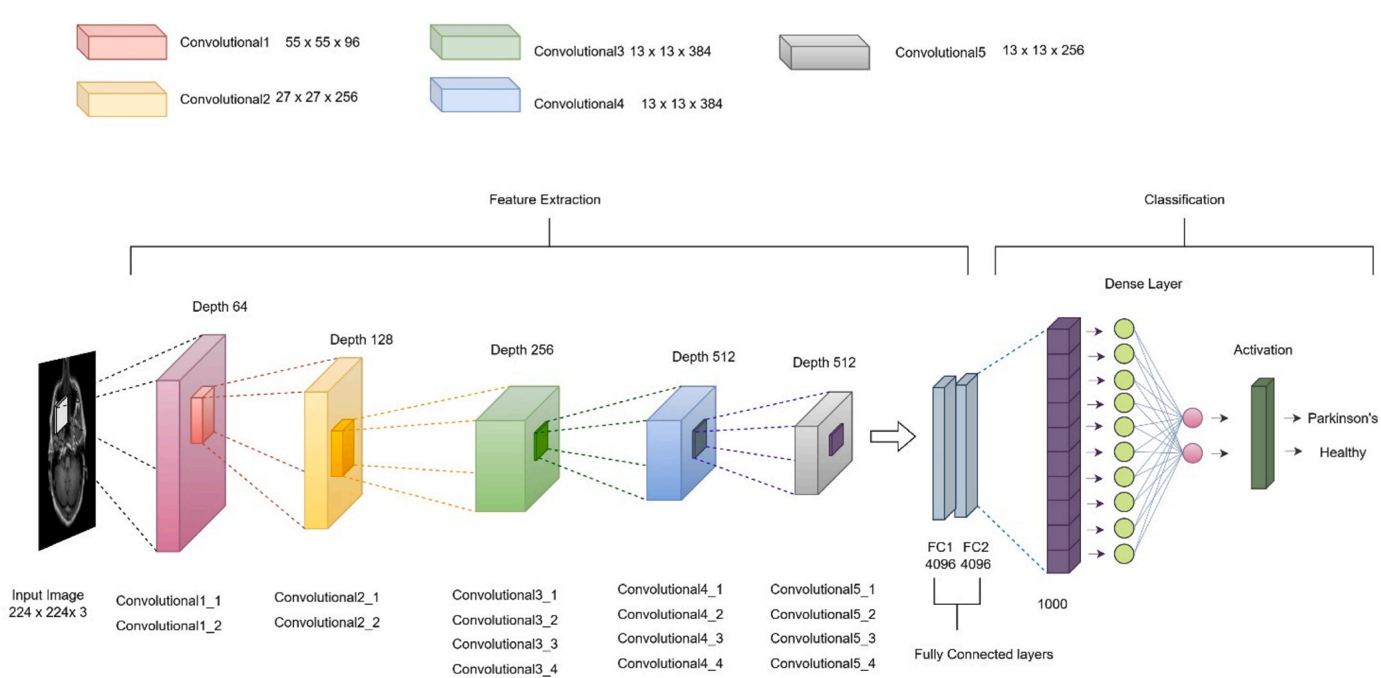



**Fig. 12.** Layer-wise microscopic analysis of the proposed VGG19 architecture.

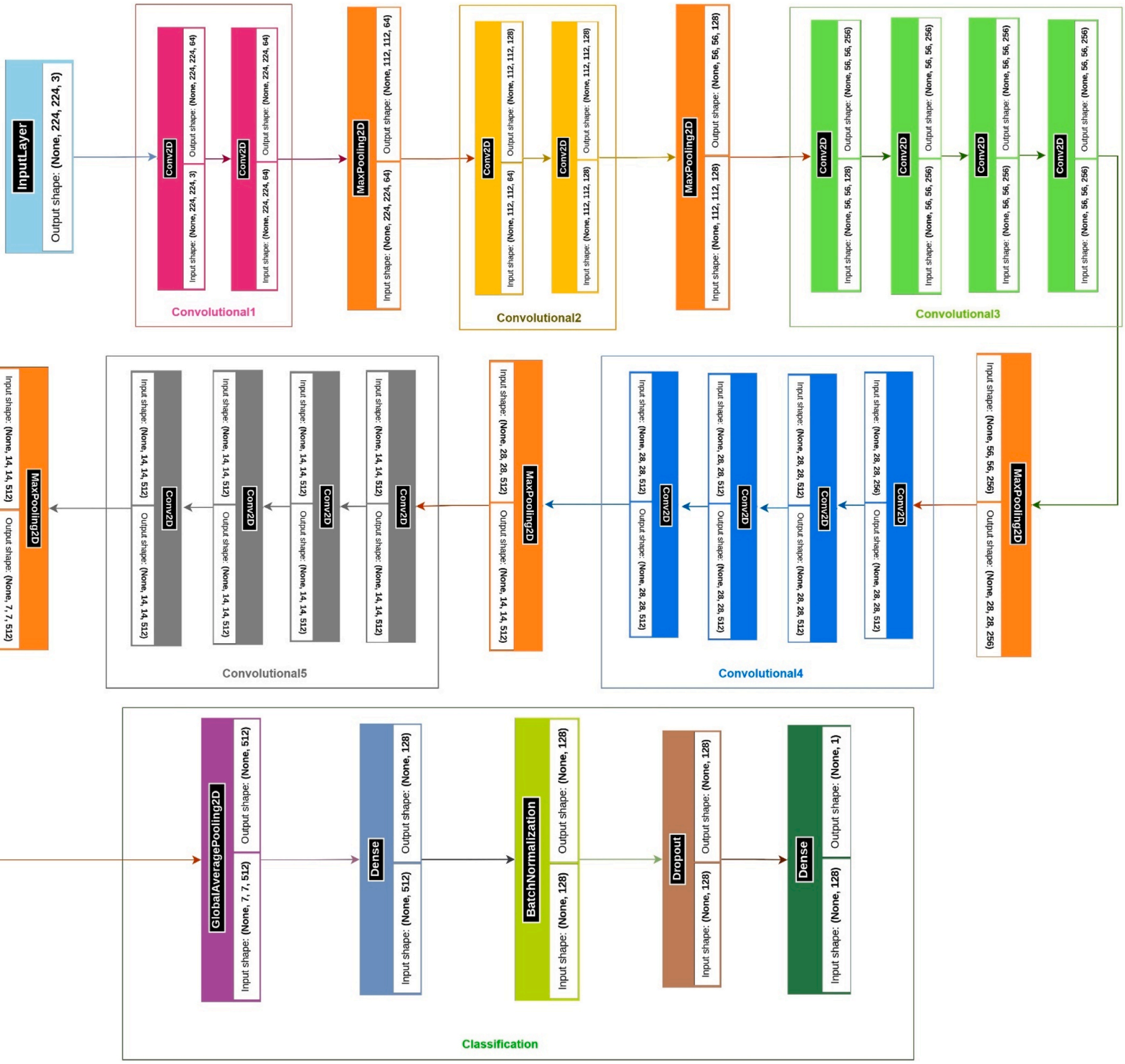



**Fig. 13.** Block diagram of the VGG19 model with modified classification layer.

where information from the input image is being extracted. In the classification part, extracted information is going through fully connected dense layer and generates outputs. Fig. 13 shows the size and dimension of each layer more precisely, showing the block diagram of the modified VGG19 architecture. The convolutional part is obtained using transfer learning where pre-trained features are achieved. The classification part has been designed manually according to the desired output using feature fusion technique. Here, data pooled from the convolutional block is given to dense layer. Data from the dense layer go through BatchNormalization and sent to another dense layer for generation output. After normalizing data droup out layer is there that disable neuron to reduce overfitting by improving generalization.

*3.3.2.2. Modified VGG19 model with feature fusion technique for disease classification with drawing data.* Using transfer learning technique, knowledge from the pre-trained models can be utilized. Initially, five CNN models were trained with the DS3 dataset. The trained models are: ResNet101, VGG19, Xception, Inception and EfficientNet. Performances of the models were evaluated and VGG19 was selected as best model for designing the final framework. Fig. 14 is showing the model selection and Feature Fusion approach to develop the modified VGG19 model.

Feature fusion (FF) refers to combining the learned features from two or more models to create a more informative and comprehensive representation. It can enhance the performance of the final classification task. Feature fusion can be used for combining two or more different types of image classification models to improve performance. FF becomes significant especially when each model captures different aspects of the data. Here, two types of image classification models have been combined using FF technique to enhance performance and advancement of the framework. Two VGG19 models were trained with spiral and wave data respectively. The models were leaded and feature maps were selected removing the classification layers from both models first. Features were concatenated and fed to a newly modified classifier. The fusion model was finally compiled and trained later. This approach of FF

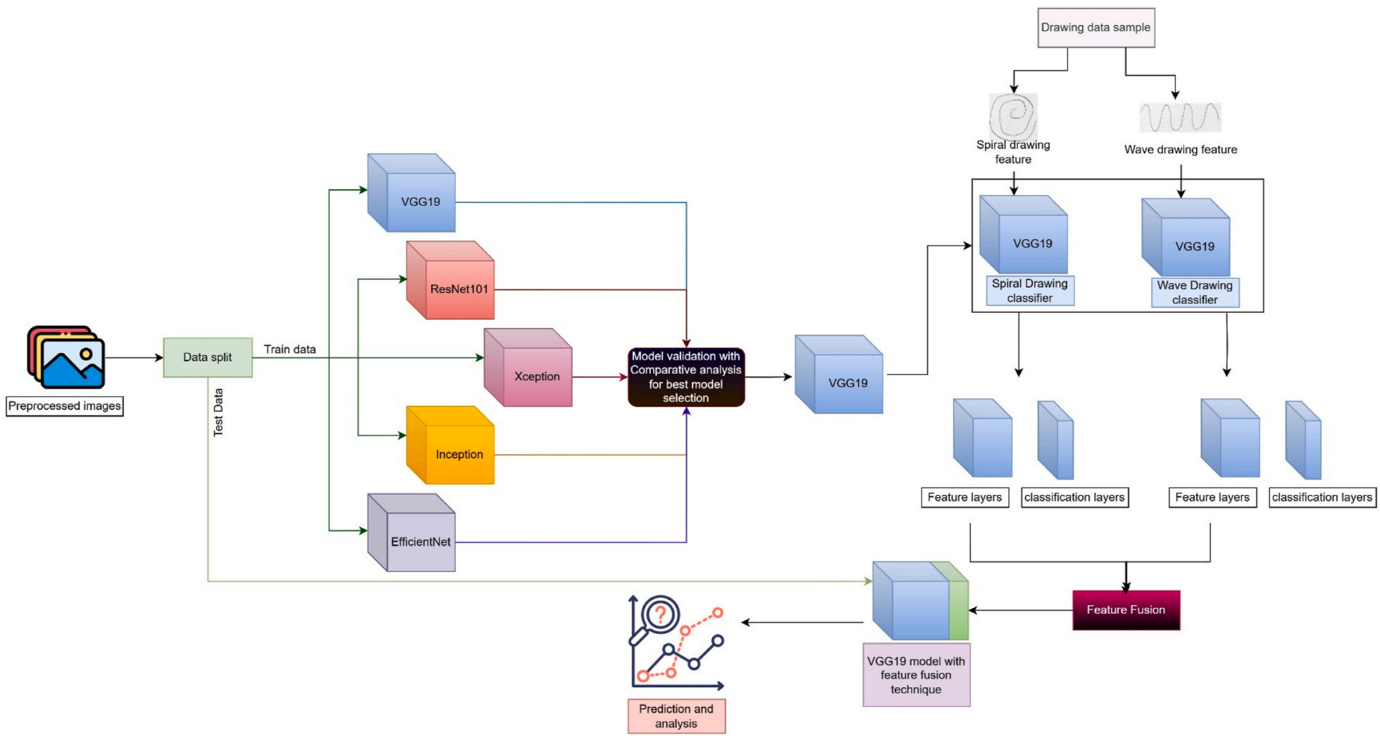



**Fig. 14.** Model selection and fusion approach for drawing data classification.

with two VGG19 models allows to combine the features learned by both models, potentially improving classification performance by capturing complementary information. This type of fusion is especially useful when different each model is trained on different aspects of the data. Implementing the fusion model, several challenges like computational complexity, alignment of feature space and overfitting issues can be handled.

Table 2 shows the architectural information of the proposed VGG19 fusion model with output shape and parameters size for respective layers.

*3.3.2.3. Hyperparameter tuning.* Hyperparameter tuning is required to enhance overall performance of the system and top reduces issues like overfitting. The values of each parameter has to be set carefully to achieve the maximum output from the models. But it is not possible to predict the optimum values for each parameter until training the models several times to check and test the overall performance. Table 3 shows the information of each parameter of the prosed models with tuned data. As the work is based on binary classification, training loss has been calculated using binary cross entropy loss function, shown in equation (4) that has been modified and adapted according to our framework requirements [49].

**Table 2**
Architectural information of the proposed VGG19 fusion model.

| Layer (type) | Output Shape | Parameters |
|---|---|---|
| vgg19 (Functional) | (None, 7, 7, 512) | 20,024,384 |
| global_average_pooling2d (GlobalAveragePooling2D) | (None, 512) | 0 |
| dense (Dense) | (None, 128) | 65,664 |
| batch_normalization (BatchNormalization) | (None, 128) | 512 |
| dropout (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 1) | 129 |

**Total params:** 20,090,689 (76.64 MB).
**Trainable params:** 66,049 (258.00 KB).
**Non-trainable params:** 20,024,640 (76.39 MB).

Table 4 shows the train loss and train accuracy of proposed spiral and wave drawing classification framework with VGG19 fusion model.

$$\text{Binary\_Crossentropy} = -(Y_{True} * \log(Y_{Pred}) + (1 - Y_{True}) * \log(1 - Y_{Pred})) \quad (4)$$

$Y_{True}$: True/Actual label
$Y_{Pred}$: Predicted probability
log: logarithm having base-e

### 3.4. Working functionality of proposed framework

Three different frameworks have been designed separately for the proposed work where the first framework is based on ML algorithms trained on DS1 dataset. Models were trained with EEG features that can classify Parkinson's disease. 2nd and 3rd frameworks are developed with DL models trained on DS2 and DS3 datasets. Theses frameworks can classify images to detect Parkinson's disease. Fig. 15 shows the flow diagram of the training and validation steps where the very first step is to load datasets to get data instances. Data are needed to be pre-processed and split into two parts-training and testing. Training data is sent to train models and test data is sent to validate the trained model performance. After training each model, it has to be saved and loaded to utilize for further usage.

### 3.5. Pseudo code

**Algorithm 1.** Classification of Parkinson's disease using ML and DL based models

The above algorithm 1 is showing the pseudo code of the proposed work where systematic logical structure is presented. Here, from loading models to predictive analysis is given with logical information. Three types of frameworks were designed here with three datasets DS1, DS2

E: Epoch number, DS1: EEG dataset for Parkinson's detection,

DS2: MRI images dataset for Parkinson detection,

DS3: Parkinson's dataset of spiral and wave drawings,

M: ML models trained with dataset DS1,

Dm: DL models trained with dataset DS2,

Di: DL models trained with dataset DS3

Input: Numerical values from DS1, MRI images from DS2, Drawing images from DS3

Output: Binary Classification (Parkinson's and normal)

Start

```
1.  Load Dataset DS1, DS2, D53
2.  Preprocess Dataset
3   Split data
4.  Model Train
5.      Train Model M with DS1
6.      Validate model M
7.      Set E = 0
8.      While E < 40:
9.          Get preprocessed image data of DS2
10.         Apply data augmentation process
11.         Pass to Model Dm
12.         Validate Model
13.         Repeat Steps
14.     End While
15.     While E < 35:
16.         Get preprocessed image data of DS3
17.         Apply data augmentation process
18.         Pass to Model Di
19.         Validate Model
20.         Repeat Steps
21. End While
22. Load Model M. Om and Di
23. Evaluate Models with test data
24. Get prediction and analysis result
End
```

**Table 3**
Parameter details of developed classification frameworks.

| Parameters | Classification with MRI data | Classification with Spiral data | Classification with Wave data | Fusion classifier for spiral and wave data |
|---|---|---|---|---|
| Train_loss | 0.033 | 0.053 | 0.061 | 0.060 |
| Train_accuracy | 96.7 | 95.4 | 92.4 | 97.7 |
| Training time | 2 h 07 min | 2 h 13 min | 1 h 39 min | 49 min |
| Epoch | 40 | 35 | 35 | 23 |
| Optimizer | Adam | Adam | Adam | Adam |
| Initial learning rate | 0.001 | 0.001 | 0.001 | 0.01 |
| Loss function | binary cross entropy | binary cross entropy | binary cross entropy | binary cross entropy |
| Output activation fn () | Sigmoid | Sigmoid | Sigmoid | Sigmoid |

and DS3. Each model comes with proper evaluation. Selected models were finalized after evaluation for predictive analysis.

### 3.6. IoMT infrastructure with proposed classification framework

The Internet of Medical Things (IoMT) refers to a network of devices that enable access to healthcare information over the internet. IoMT devices can share data remotely, process it online, and provide wireless access. This technology plays a crucial role in telemedicine, allowing individuals to receive healthcare services remotely.

**Table 4**
Train accuracy and train loss values of drawing data based classification framework.

| Epoch | Train loss for spiral drawing framework with VGG19 | Train accuracy for spiral drawing framework with VGG19 | Train loss for wave drawing framework with VGG19 | Train accuracy for wave drawing framework with VGG19 |
|---|---|---|---|---|
| 1 | 25.9 | 75.9 | 22.9 | 87.9 |
| 2 | 29.2 | 65.4 | 28.2 | 54.4 |
| 3 | 29.6 | 71.2 | 45.6 | 81.2 |
| 4 | 35.9 | 70.8 | 34.9 | 65.8 |
| 5 | 39.2 | 75.6 | 49.2 | 80.6 |
| 6 | 37.6 | 59.4 | 39.6 | 59.4 |
| 7 | 46.1 | 65.1 | 51.1 | 75.1 |
| 8 | 49.9 | 68.0 | 57.9 | 70.0 |
| 9 | 56.7 | 45.5 | 62.7 | 61.5 |
| 10 | 61.2 | 46.1 | 54.2 | 72.1 |
| 11 | 59.6 | 44.4 | 66.6 | 58.4 |
| 12 | 66.5 | 40.7 | 56.5 | 45.7 |
| 13 | 68.5 | 42.2 | 75.5 | 49.2 |
| 14 | 69.4 | 38.8 | 60.4 | 52.8 |
| 15 | 72.6 | 30.6 | 78.6 | 30.6 |
| 16 | 74.5 | 31.5 | 62.5 | 35.5 |
| 17 | 75.2 | 33.4 | 70.2 | 27.4 |
| 18 | 79.7 | 33.7 | 79.7 | 37.7 |
| 19 | 81.1 | 29.8 | 81.1 | 22.8 |
| 20 | 84.5 | 31.5 | 73.5 | 28.5 |
| 21 | 84.7 | 30.9 | 86.7 | 13.9 |
| 22 | 85.5 | 21.3 | 82.5 | 21.3 |
| 23 | 86.4 | 23.2 | 88.4 | 24.2 |
| 24 | 87.3 | 16.4 | 83.3 | 16.4 |
| 25 | 89.8 | 19.8 | 89.8 | 19.8 |
| 26 | 91.5 | 19.4 | 85.5 | 25.4 |
| 27 | 92.9 | 15.4 | 89.9 | 9.4 |
| 28 | 93.6 | 13.7 | 90.6 | 13.7 |
| 29 | 93.8 | 11.6 | 89.8 | 6.6 |
| 30 | 94.3 | 9.8 | 91.3 | 12.8 |
| 31 | 94.6 | 6.2 | 88.6 | 6.2 |
| 32 | 95.1 | 5.4 | 91.1 | 5.4 |
| 33 | 95.3 | 5.4 | 91.3 | 5.4 |
| 34 | 95.4 | 5.3 | 91.4 | 5.3 |
| 35 | 95.4 | 5.3 | 92.4 | 5.3 |

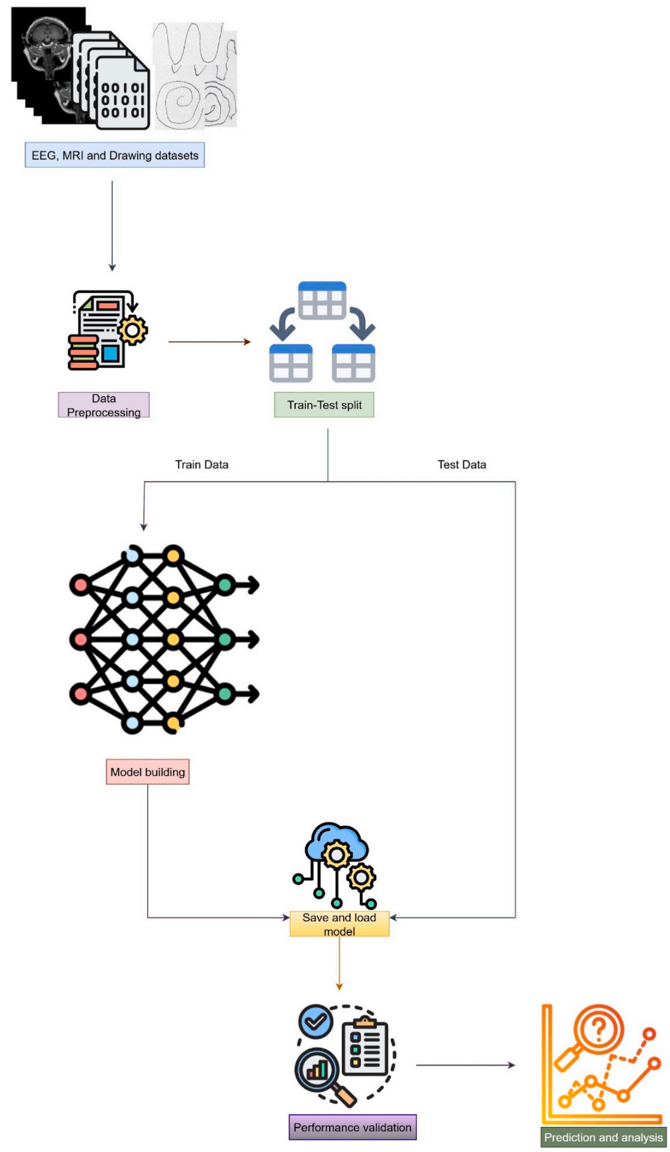



**Fig. 15.** Flow diagram of proposed approach.

The main aim of this research is to design and development of ML and DL models to classify the Parkinson disease accurately and efficiently. Nevertheless, such models are actually useful in a real-world healthcare setting. In that aspect, an IoT-based framework may be a viable addition, where wearable and sensor-equipped devices continuously gather patient data and the trained ML/DL models process it in real-time to facilitate diagnosis and monitoring. This integration will help bridge gaps between computational research and clinical application so that the suggested classification models could be converted into scalable, accessible, and patient-centric solutions. Fig. 16 shows the IoMT infrastructure where cloud-based classification and tele healthcare approaches have been presented. Patients can send the medical image directly to the cloud server to get the remote services from the healthcare experts. Central clod system is integrated with proposed classification framework that can classify the received image. The main cloud server systems process classified medical images to derive valuable insights. Explainable AI provides clear and interpretable information to enhance decision-making. Doctor lists are organized according to image classifications and shared with appropriate healthcare providers.

Feedback from healthcare providers is transmitted back to users, ensuring smooth communication and care delivery.

The figure depicts a distributed network system linked to a central cloud server, accessible to users via the internet. The cloud server incorporates an advanced AI module, which houses our proposed algorithm. When MRI images are uploaded from any source to the cloud server, they are immediately classified and forwarded to the appropriate healthcare facilities based on the classification results. To provide a clear understanding, the figure highlights three sources of MRI data transmission: hospitals, personal IoMT devices, and diagnostic laboratories. Regardless of the source, the MRI images are transmitted to the cloud server through the internet for processing. Upon receiving the images, the AI module processes them following the steps outlined in the figure. These steps involve classifying the images to determine the dementia level. The integrated AI module features a specialized classification framework designed to accurately identify dementia levels from MRI scans. Initially, the received images are resized to meet the input dimensions required by the classification model. Once resized, the images are processed through the classification framework, generating precise diagnostic results. These results, along with the images, are then sent to the appropriate recipients, such as healthcare professionals, research centers, or hospitals. Responses or feedback from these recipients—-whether from hospitals, research labs, or individual physicians—are subsequently routed back to the end users. This ensures efficient communication and a continuous flow of information between the users and the healthcare providers.

This infrastructure enables individuals to receive reliable assessments of their dementia levels while also gaining access to expert advice and recommendations from healthcare professionals remotely. By eliminating the need for physical visits, the system facilitates timely medical insights and enhances the accessibility of healthcare services, particularly in scenarios where in-person consultations may be difficult.

## 4. Results and discussion

In this section, performances of the proposed framework have been presented where quantitative and qualitative analysis have been done, discussed the obtained results, and compared the outcomes with other state-of-the-art techniques.

### 4.1. Quantitative analysis

In this subsection, performances of the models have been presented in quantitative measurements. The subsection is categorized into two parts for ML and DL based frameworks where training and testing results have been given in form of tables, graph or charts and discussed accordingly.

#### 4.1.1. Performance analysis of ML based framework

Seven ML models have been trained on DS1 data instances and listed the accuracy details for training and testing which has been shown in Table 5. Analyzing the values from Tables 5, it can be observed that LR performed with better results than other models during both training and testing phases. Fig. 17 (a) shows the confusion matrix of LR where values of true and predicted labels are given. Fig. 17 (b) shows the performance metrics obtained by LR, where accuracy, precision, recall and F1 scores are shown.

#### 4.1.2. Performance analysis of DL based frameworks

Five CNN models have been trained with DS2 and DS3 data instances, among which VGG19 showed promising performance for classification of MRI and Drawing images. Fig. 18 (a) shows the confusion matrix and Fig. 18 (b) presents the performance metrics of the VGG19 based framework that has been designed for MRI image classification for Parkinson's disease detection. Fig. 19 (a) shows the confusion matrix of the VGG19 model that has been used for Spiral drawing classification framework where performances metrics are presented by Fig. 19 (b).

Confusion matrix for the VGG19 model used in wave drawing classification framework is presented by Fig. 20 (a) and comparison of performance metrics is given in Fig. 20 (b).

#### 4.1.3. Validation and comparative analysis

Table 6 presents the performance status of ML models trained with the DS1 dataset where LR model offers high accuracy with 90:10 train-test split ratio. Table 7 shows the 5-fold cross validation method where accuracy for each five split with mean and Standard deviation (Std.) values are presented. Standard deviation shows the dispersion of data, which is calculated using the adapted modified formula shown in equation (5) [60].

$$Std = \sqrt{\frac{1}{T-1}\sum_{i=1}^{T}(m_i - \overline{m})^2} \tag{5}$$

For MRI column in Table 7, standard deviation can be calculated doing the following steps using the formula:

Total elements, T = 5.

Sum of the elements, $\sum m = 446.2$.

Mean/arithmetic average of the elements, $\overline{m} = 89.24$

Variance, $(Std_{MRI})^2 = 9.593$

$$Std_{MRI} = \sqrt{\frac{1}{5-1}\sum_{i=1}^{5}(m_i - \overline{m})^2}$$

$$\begin{aligned}(Std_{MRI})^2 &= \frac{\sum(m_i - \overline{m})}{5-1} \\ &= \frac{(85.1-89.24)^2 + \ldots + (92.8-89.24)^2}{4} \\ &= \frac{38.372}{4} \\ &= 9.593\end{aligned}$$

$$\begin{aligned}Std_{MRI} &= \sqrt{9.593} \\ &= 3.097 \approx 3.1\end{aligned}$$

Following the same procedure, standard deviation of EEG, Spiral and Wave based models have been calculated.

Table 8 is showing the performance metrics analysis for each developed classification framework. All the three frameworks developed with three distinct datasets offer descent performance with high accuracy, precision, recall, specificity, and F1 Score. Besides the basic evaluation measurements, we also calculated AUC-ROC and Cohen Kappa to enhance reliability of the models. As presented in Table 8, the AUC-ROC scores were relatively stable across all datasets (0.9480.982), which confirmed high ability of the proposed framework to be discriminative. The Kappa scores (0.86–0.93) of Cohen showed that there was a high level of agreement other than chance. Moreover, A paired *t*-test has been conducted to show the comparison between the performances of each framework. The obtained p-values for EEG-based, MRI-based, spiral image-based, and wave image-based frameworks are 0.021, 0.013, 0.018 and 0.034 respectively. All the achieved p-values are lesser than the significance threshold (0.05), which indicates that the proposed frameworks provide statistically significant improvements over the baseline.

### 4.2. Qualitative analysis

This subsection deals with the qualitative analysis of the performance obtained by the proposed work. Fig. 21(a) shows the feature importance for LR model trained with DS1 instances. The feature names are shown in the X-axis and coefficient is shown in Y-axis. Fig.21 (b) shows the ROC curve of the LR model where X-axis is indicating False

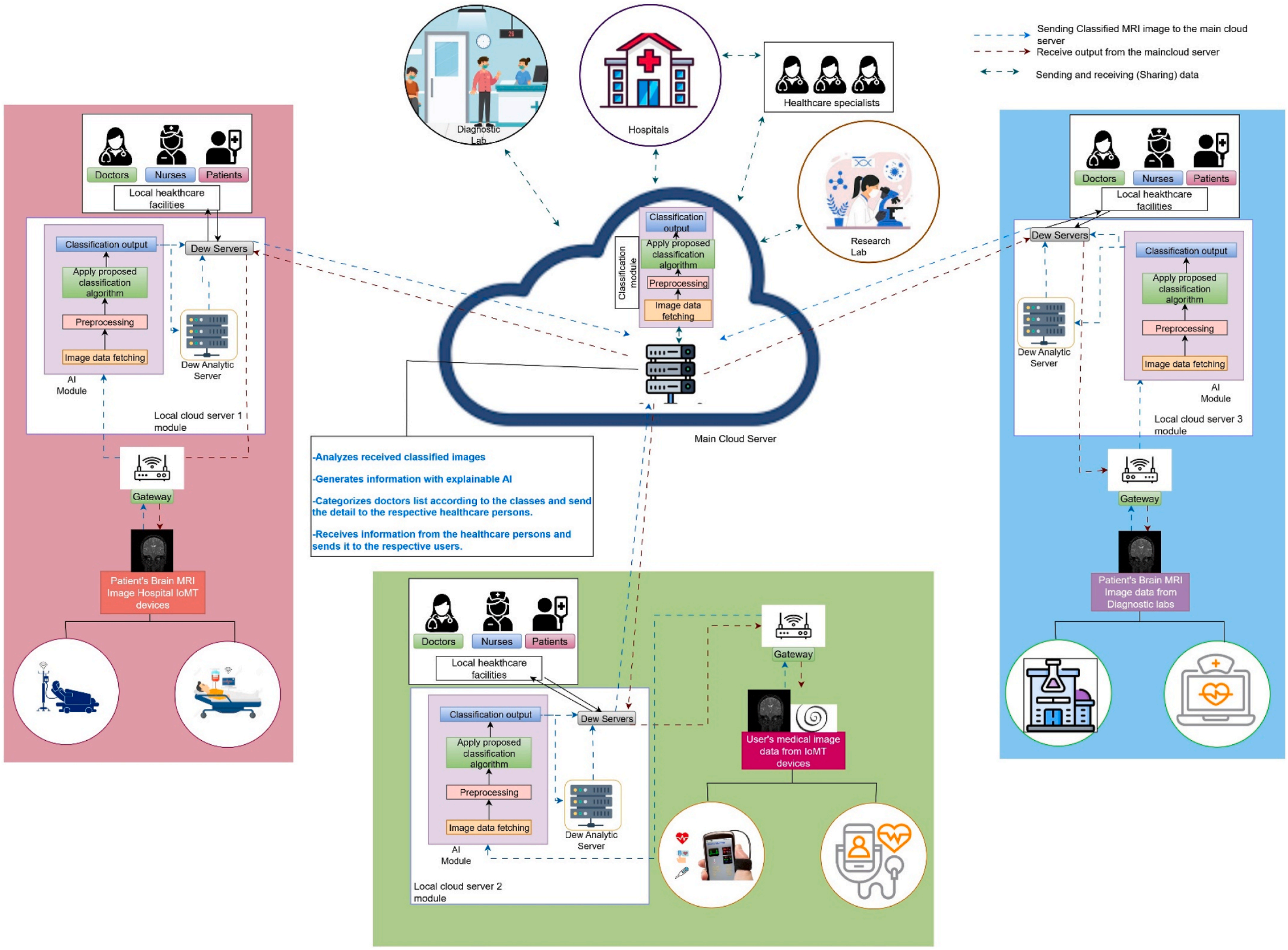



**Fig. 16.** Proposed IoMT infrastructure integrated with developed classification approach.

Positive rate and Y-axis is showing True Positive rate. Accuracy graph of seven ML models with different training size is given in Fig. 22 (a). Here, it can be observed that LR model achieves more than 95 % of accuracy with 90:10 ratio.

Fig. 22 (b) shows the accuracy status of the five models trained for the same framework. From beginning to the end, VGG19 showed promising performance better than other models that made it to be considered as the best model for the final framework. Fig. 23 shows the accuracy and loss graph of VGG19 for MRI images classification framework where accuracy and loss status is presented with epoch variations. X-axis is represented as epoch numbers and Y-axis is indicating accuracy and loss values. Initially loss was very high and accuracy was very low with the very first epoch. With increasing the number of epochs, loss got decreased and accuracy got increased. At the 40th epoch, highest accuracy with minimum loss was achieved and up to that number, epoch was set as ideal for training.

Fig. 24 (a) and 24 (b) is showing the accuracy and loss graph of VGG19 model used for spiral and wave drawings classification respectively. Initially losses were high and accuracy values were less in both graphs. At 35 epoch, highest accuracy was obtained with low loss.

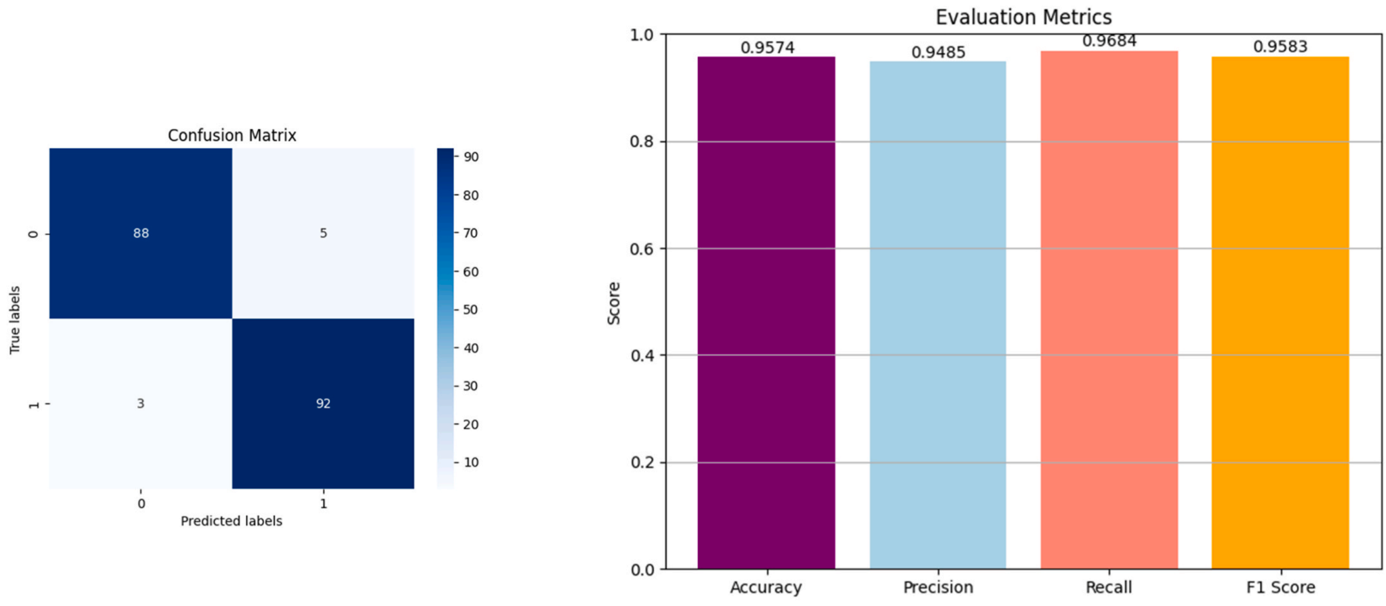
Fig. 25 is showing the accuracy and loss graph of the proposed modified fusion model of VGG19 that have been trained for classifying drawing data for Parkinson's disease detection.

**Table 5**
Training and testing accuracies obtained by ML models.

| ML Models | Training Accuracy (%) | Testing Accuracy (%) |
|---|---|---|
| LR (Logistic Regression) | 95.3 | 95.7 |
| SVM | 81.2 | 79.3 |
| KNN | 85.4 | 86.9 |
| Random Forest | 86.8 | 87.4 |
| Perceptron | 83.1 | 82.7 |
| XGBoost | 90.7 | 92.4 |
| Decision Tree | 81.8 | 85.2 |

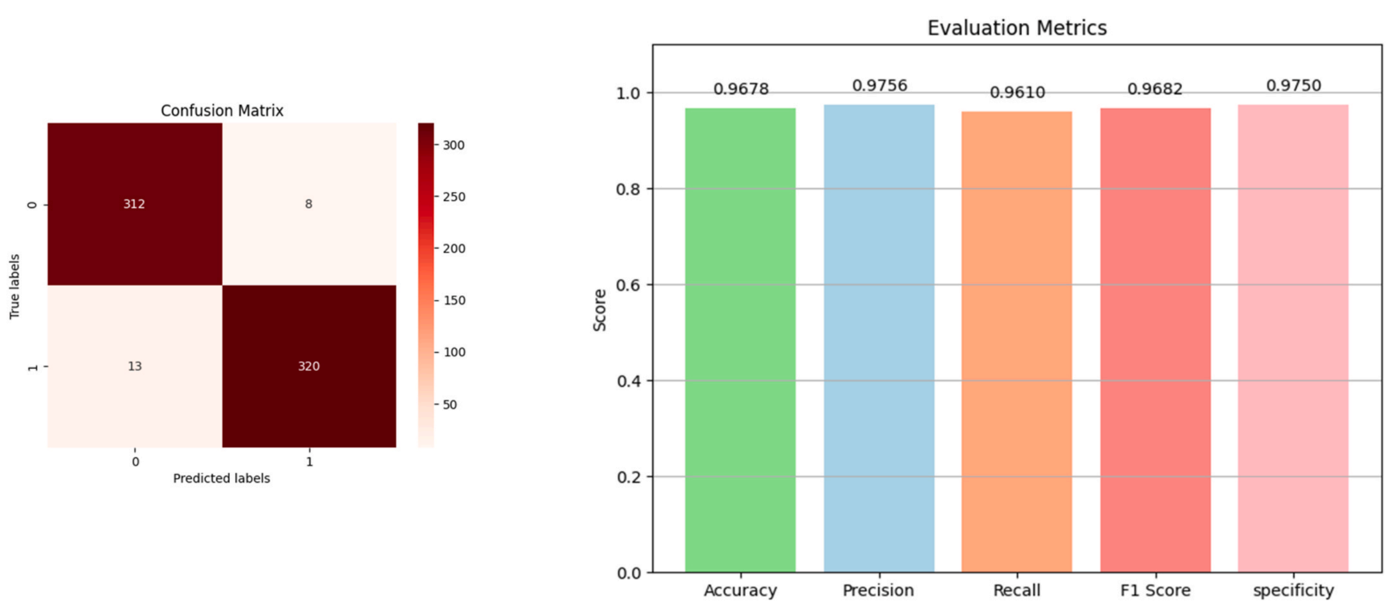
### 4.3. Discussion

To the best of our knowledge, this work is that comes with high accuracy, efficiency, and reliability. In recent years, various frameworks have been designed to detect PD, but those systems have different flaws including, data limitation, lack of authentic data, appropriate model selection, proper comparison with state-of-the-art techniques etc. To support the strengths and novelty of our work, a comparative analysis has been done showing in Table 9 that presents the comparison between the proposed work with other existing state-of-the-art works. Cui et al. (2024) proposed a MHAN-based framework where 6120 images were used. The work comes with 94.11 % of accuracy [73].




**(a)** **(b)**

**Fig. 17.** (a) Confusion matrix of the trained LR model, **(b)** Performance metrics obtained by LR model trained with DS1 dataset.




**(a)** **(b)**

**Fig. 18.** (a) Confusion matrix of VGG19 trained for MRI image classification based framework, **(b)** Performance metrics of MRI classification framework.

Suuronen et al. (2023) worked on EEG setup where 309 EEG samples were utilized [76]. Demir et al. (2021) used LSTM models with 756 image samples that ensures 94.27 % of accuracy [78]. Shuqair et al. (2024) proposed RL and LSTM based framework analyzing the recorded data. The work comprises of 82.94 % of accuracy [80]. Igene et al. (2023) proposed on ML models, worked on 34 patients to collect healthy and PD images for model training [83]. Gupta et al. (2023) used traditional ML models to build a detection framework what came with 92.30 % of accuracy [86]. Smolik et al. (2024) [87] proposed a transformer-based model where 59 subjects have been utilized with only 58 % of accuracy. Our proposed framework is comprised of both ML and DL based architectures to detect PD on different factor with early and accurate manner. Seven ML models were trained on EEG data where five powerful DL models were trained for MRI image and drawing data classification. Feature Fusion method has been applied to build such a classification model architecture that is accurate, efficient as well as robust. The accuracy of the ML based framework is 94.75 %. MRI image-based PD classification framework comes with 96.78 % of accuracy. 95.69 and 92.27 % of accuracies are achieved form spiral and wave drawing-based classification frameworks respectively. The proposed fusion model comes with 97.7 % of accuracy which is better than other existing works as far best of our knowledge. 6502 (MRI), 6725 (Spiral Drawing), 3969 (Wave Drawing) images and 756 (EEG Recording) instances have been used to train models for the proposed framework

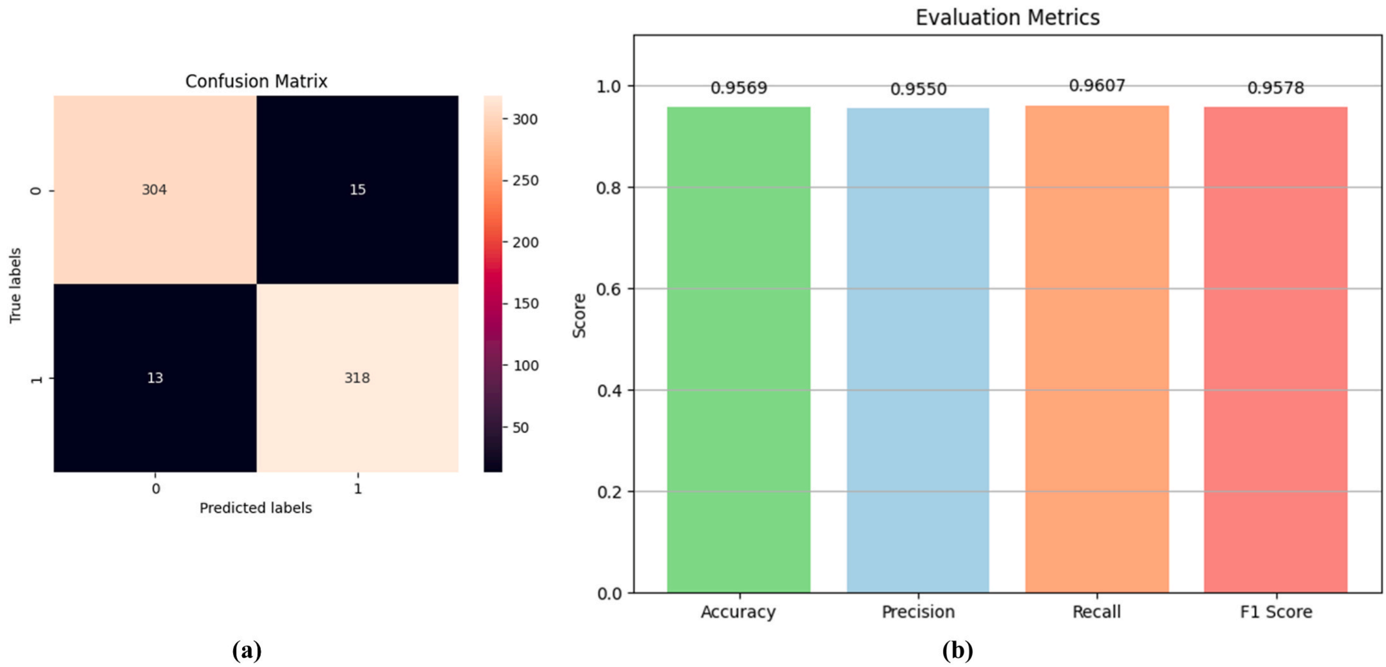



**Fig. 19.** (a) Confusion matrix of VGG19 for Spiral drawing based classification framework, **(b)** Performance metrics of Spiral drawing based classification framework.

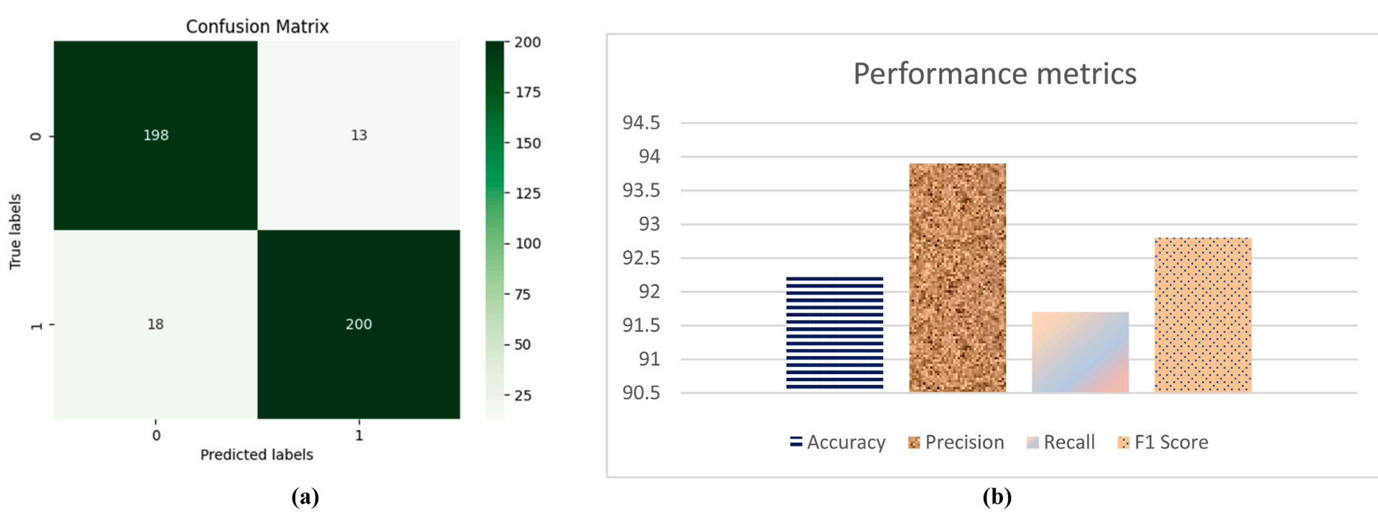



**Fig. 20.** (a) Confusion matrix of modified VGG19 for wave drawing based classification framework, **(b)** Performance metrics of wave drawing based classification framework.

**Table 6**
Performance status of ML models with different split ratio.

| Train–Test Ratio in ML | Accuracy with Logistic Regression | Accuracy with SVM | Accuracy with KNN | Accuracy with Random Forest | Accuracy with Perceptron | Accuracy with XGBoost | Accuracy with Decision Tree |
|---|---|---|---|---|---|---|---|
| 90:10 | 95.7 | 79.3 | 86.9 | 87.4 | 82.7 | 92.4 | 85.2 |
| 80:20 | 89.4 | 75.9 | 82.7 | 84.5 | 76.8 | 87.5 | 79.4 |
| 70:30 | 82.6 | 67.1 | 71.8 | 77.8 | 70.3 | 80.3 | 72.3 |
| 60:40 | 71.8 | 62.7 | 63.6 | 69.5 | 62.8 | 68.1 | 68.1 |
| 50:50 | 62.5 | 60.1 | 59.4 | 60.7 | 57.6 | 61.4 | 60.5 |
| 40:60 | 61.7 | 56.3 | 51.4 | 58.2 | 55.2 | 53.6 | 59.4 |

**Table 7**
5 fold cross-validation method for performance analysis of different classification frameworks.

| Split Count | DS2 (MRI) | DS3 (Spiral) | DS3 (Wave) | DS1 (EEG) |
|---|---|---|---|---|
| 1 | 85.1 | 87.4 | 89.2 | 93.3 |
| 2 | 91.4 | 88.3 | 81.3 | 88.4 |
| 3 | 89.6 | 84.5 | 84.6 | 91.6 |
| 4 | 87.3 | 91.2 | 87.6 | 90.2 |
| 5 | 92.8 | 92.7 | 87.5 | 92.7 |
| Arithmetic Mean | 89.2 | 88.8 | 86.0 | 91.24 |
| Standard deviation (std.) | 3.1 | 3.2 | 2.8 | 1.9 |

**Table 8**
Performance metrics obtained from the proposed EEG data, MRI images, Spiral and wave drawing based classification framework.

| Performance metrics | DS1 (EEG) | DS2 (MRI) | DS3 (Spiral) | DS3 (Wave) |
|---|---|---|---|---|
| Accuracy | 95.7 | 96.7 | 95.6 | 92.27 |
| Precision | 94.8 | 97.5 | 95.5 | 93.9 |
| Recall | 96.8 | 96.1 | 96.0 | 91.7 |
| Specificity | 94.6 | 97.5 | 95.3 | 93.8 |
| F1 Score | 0.958 | 0.968 | 0.957 | 0.928 |
| AUC-ROC | 0.975 | 0.982 | 0.971 | 0.948 |
| Cohen's Kappa | 0.91 | 0.93 | 0.90 | 0.86 |
| *t*-test (p-value vs. baseline) | 0.021 | 0.013 | 0.018 | 0.034 |

development. It is possible to improve the clinical impact of the proposed fusion DL-based frameworks by incorporating them into an IoT-enabled environment. Although the DL models proved to be very accurate and robust in EEG, MRI, and spiral-wave data, their real utility can be observed when used in real-life healthcare situations. The patient data can be gathered continuously in real-time through wearable and sensor-based devices integrated with IoT to transmit the patient data to the trained models and enable early detection, remote supervision, and prompt clinical responses. It is not only safe and scalable, but also fills the gap between the research-based classification models and the practical, patient-centered healthcare solutions.

Our findings have clear and immediate clinical relevance because they demonstrate that a carefully engineered, multi-modal AI pipeline, combining EEG features, structural MRI, and drawing-based biomarkers, can markedly improve diagnostic sensitivity and specificity over single-modality approaches and therefore meaningfully augment current clinical workflows. Recent reviews and large-scale studies reinforce that ML applied across diverse PD data types increases diagnostic yield and supports earlier detection, which is essential for timely enrolment into neuroprotective trials and for earlier initiation of symptomatic and rehabilitative interventions [91]. At the bedside and in telemedicine settings, an integrated AI system like ours could be used as a triage and longitudinal-monitoring tool: (1) to flag individuals who warrant expedited specialist review, (2) to quantify motor and non-motor change between visits, and (3) to supply objective measures that complement clinical rating scales, thereby reducing subjectivity in early or atypical presentations. Importantly, modality-specific advantages documented in recent work support our architecture: spiral/handwriting analyses using transfer-learning approaches reliably capture fine motor impairment and tremor signatures that are difficult to quantify clinically, making drawing assessments a low-cost, high--yield adjunct for community screening [92]. EEG features, when processed with modern channel-attention and deep-feature pipelines, have also been repeatedly shown to contain discriminative biomarkers of PD and to strengthen detection when combined with imaging or behavioral data, aligning closely with the gains we observed in the performance of EEG-based model [93]. Finally, structural and advanced MRI-based models provide complementary, anatomy-anchored evidence for neurodegeneration and can improve specificity in differentiating PD from atypical parkinsonian syndromes, supporting the inclusion of MRI in a multimodal diagnostic stack for higher clinical confidence [94].

Despite these strengths, important limitations temper immediate clinical translation. First, most high-performing AI PD studies including components of our own work rely on curated or augmented datasets; external generalizability to diverse clinical populations (different scanners, languages, handwriting styles, comorbidities, and ethnic groups) remains insufficiently validated. Second, the computational and data-management demands of multi-modal fusion and cloud-based IoMT deployment raise pragmatic barriers for resource-limited clinics: inference latency, model size, and secure data transfer must be optimized before routine use. Third, clinical utility depends not only on diagnostic accuracy but on longitudinal performance (prediction of progression, medication ON/OFF states, and response to interventions); most available cross-sectional datasets and many published models provide

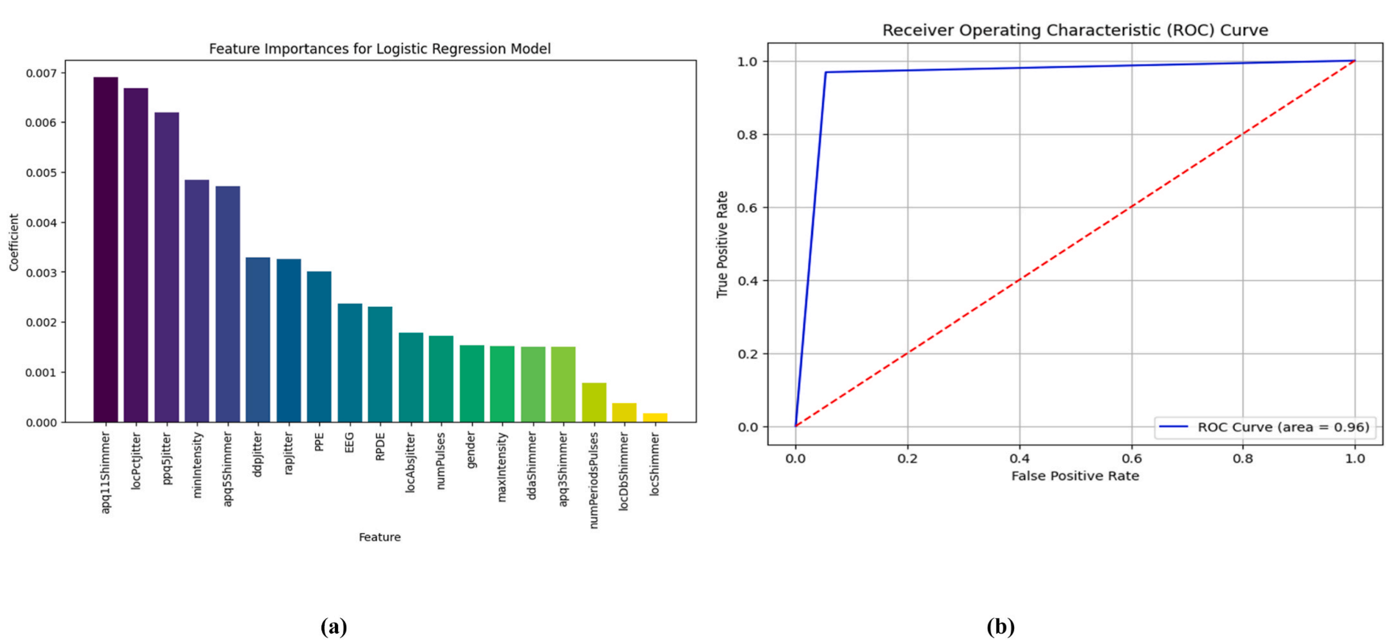
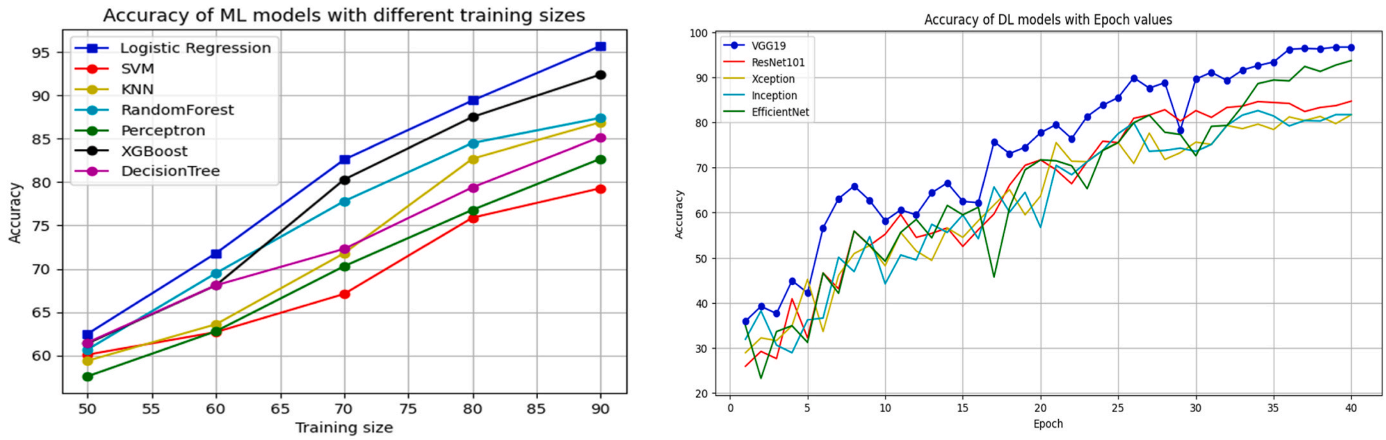



**Fig. 21.** (a) Feature importance graph for LR model, **(b)** RoC curve generated with LR model.




**(a)** **(b)**

**Fig. 22.** (a) Accuracy graph for ML models trained with DS1 data, **(b)** Accuracy graph for all DL models used in MRI image-based classification framework.


**Fig. 23.** Accuracy and loss graph generated obtained by VGG19 for MRI classification-based framework.

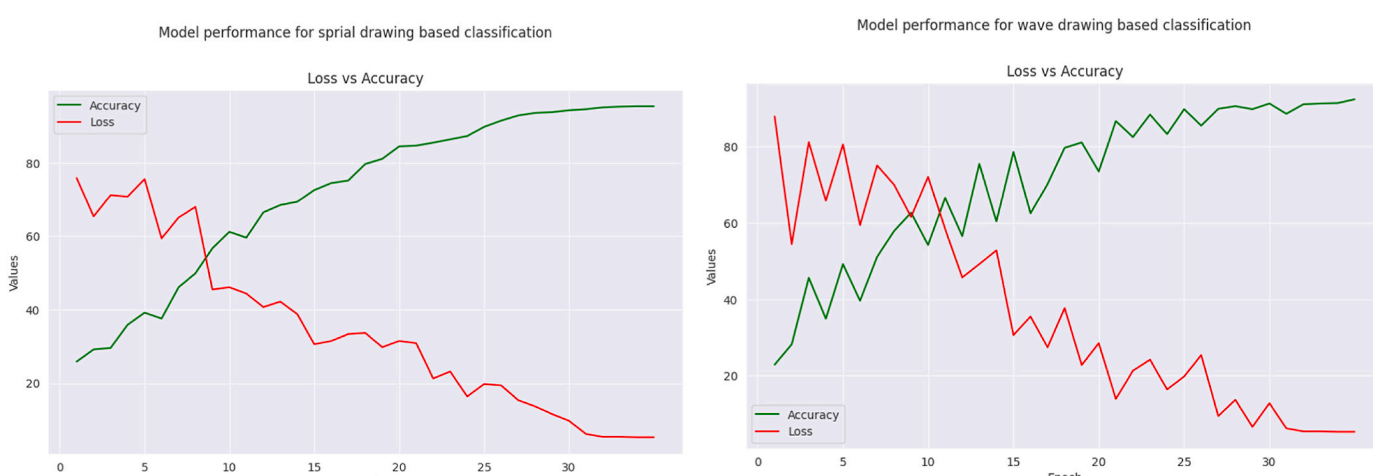



**Fig. 24.** (a) Accuracy and loss graph for spiral drawing-based classification framework, **(b)** Accuracy and loss graph for wave drawing based classification framework.

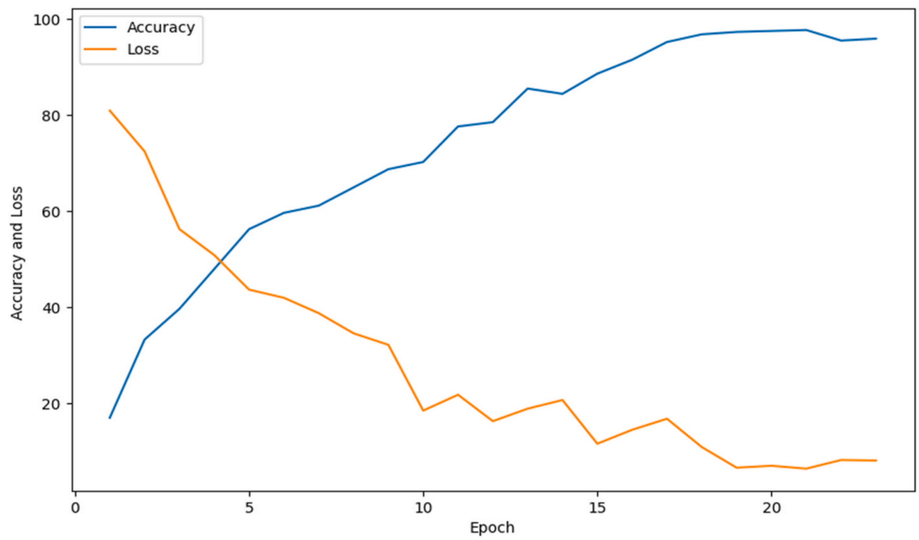



**Fig. 25.** Accuracy and loss graph for fusion VGG19 modified model.

**Table 9**
Comparative analysis between proposed work and existing state-of -the-art works.

| Author(s) | Model Used | Total Images | Accuracy |
|---|---|---|---|
| Cui et al. (2024) [73] | MSHANet (Multiscale-Hybrid Attention Network) | 6120 images | 94.11 % |
| Suuronen et al. (2023) [76] | Minimal EEG setup | 309 EEG samples | 76 % |
| Demir et al. (2021) [78] | LSTM with image-mapped features | 756 samples | 94.27 % |
| Shuqair et al. (2024) [80] | RL + LSTM | 12 Subjects (PD1) and 7 Subjects (PD2) recordings | 82.94 % F1 (PD1) 76.67 F1 (PD2) |
| Igene et al. (2023) [83] | Machine learning | 17 PD and 17 Healthy Patients | 92.6 %–94.4 % |
| Gupta et al. (2023) [86] | Machine learning (SVM, RandomForest, KNN, XGB) | 195 Voice Recordings | 92.30 % |
| Smolik et al. (2024) [87] | Wav2Vec 2.0 (transformer-based) | 59 Subjects | 58 % |
| Proposed Model | ML Models: Logistic Regression, SVM, KNN, Random Forest, Perceptron, XGBoost, Decision Tree | 6502 (MRI) | ML: 95.74 % |
| | DL Models: ResNet101, VGG19, Xception, Inception, EfficientNet | 6725 (Spiral Drawing) | MRI: 96.78 % |
| | Final mode: Logistic Regression and Fusion VGG19 modified | 3969 (Wave) | Spiral: 95.69 % |
| | | 756 (EEG Recording) | wave: 92.27 % Fusion model: 97.7 % |

limited evidence on these trajectories. Fourth, while deep models deliver high numeric performance, their relative opacity conflicts with clinicians' need for interpretable, verifiable evidence unless paired explainability layers are implemented. Finally, regulatory, privacy, and ethical frameworks for AI-driven diagnostics (consent, data ownership, algorithmic bias mitigation) are evolving and will need alignment before broad clinical adoption. These caveats are also emphasized across the contemporary literature discussing IoMT and AI deployment in neurodegeneration [95].

To address these limitations and accelerate translational impact, future work should pursue three concurrent paths. First, prospective, multi-center validation studies must be prioritized: collecting harmonized, demographically diverse cohorts with standardized acquisition protocols will permit calibration, recalibration, and external validation of fusion models and will reduce overfitting to site-specific artifacts. Second, expand the modality palette and temporal scope, integrating passive wearable/smartphone digital biomarkers, blood-based proteomic signatures, and continuous home-monitoring data, because recent advances show that combining peripheral biomarkers with behavioral and imaging data can detect PD earlier and track progression more robustly than any single source [91]. Third, emphasize model practicality and trust: develop lightweight on-device or edge-computing variants for low-resource settings, incorporate explainable AI modules that produce clinician-readable rationales (saliency maps, key feature attributions, example-based explanations), and embed uncertainty estimates so outputs can be weighed appropriately in clinical decision making. Parallel research should evaluate clinical-utility endpoints (time to diagnosis, impact on trial recruitment, changes in management, patient outcomes) rather than only classification metrics. On the technology horizon, hybrid paradigms that combine classical ML interpretability with the representational power of deep fusion networks, and emerging solutions for privacy-preserving learning (federated learning, differential privacy), offer practical routes for multi-center model improvement without raw data sharing. Collectively, these directions will help convert the promising accuracy reported here into reliable, ethical, and equitable tools that meaningfully change clinical care for people with PD.

## 5. Conclusion

In conclusion, PD continues to be a global health problem because of the progressive nature of the disease and its effects on patients' functioning and self-care capabilities. Thus, the detection of PD is pivotal from the early stages and accurate differentiation from other neurodegenerative disorders. Implementation of technologies, for instance, ML and DL, to enhance the visualization of PD-specific patterns, especially by image-based frameworks. Even simple models such as decision trees and SVMs, alongside profound DL models including VGG19, ResNet101 and EfficientNet, have registered fair potentiality for boosting the diagnostic precision. Proposed work presents a solution to detect PD in a very efficient and accurate way where classification frameworks have been designed with advanced and optimized AI-driven models. The proposed work ensures accuracy and reliability where 95.74 % of accuracy have been achieved with ML based framework and DL based framework has been developed with 97.7 % of accuracy with fusion VGG19 model. In future, Reinforcement learning technique can be used in classification framework and advanced AI-based approaches using generative algorithms and ensemble learning technique can be utilized. Metaheuristic algorithms can be used to make the models more optimized. The proposed work can be helpful for further research in healthcare as well as related technical fields.

## CRediT authorship contribution statement

**Gouri Shankar Chakraborty:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Joy Chakra Bortty:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Joy Das:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Inshad Rahman Noman:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Kanchon Kumar Bishnu:** Writing – review & editing, Visualization, Formal analysis, Data curation, Conceptualization. **Araf Islam:** Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization.

## Data availability statement

The data presented in this study are openly available in Kaggle: "Parkison Diseases EEG Dataset" at https://www.kaggle.com/datasets/s3programmer/parkison-diseases-eeg-dataset [88]. "NTUA_prakinson_MRI" at https://www.kaggle.com/datasets/shayalvaghasiya/ntua-prakinson [89]. "Parkinson's Drawings" at https://www.kaggle.com/datasets/kmader/parkinsons-drawings [90].

## Ethical Statement for intelligence-based medicine

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

I agree with the above statements and declare that this submission follows the policies of Solid State Ionics as outlined in the Guide for Authors and in the Ethical Statement.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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