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A Novel Approach for Neurodegenerative Disorders Classification Using Hybrid Deep Convolutional Neural Network (CNN) Probabilistic Classifier

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This study employs a hybrid Deep Convolutional Neural Network (CNN) Probabilistic Classifier to automatically categorize and predict neurological illnesses such as retinal disease, Parkinson's, and Alzheimer's. This technique combines increased retinal layer segmentation with classification algorithms to address early diagnosis and prognosis of common illnesses. Combining CNN feature extraction capabilities with probabilistic models such as Bayesian networks improves forecast accuracy and understandability. This hybrid strategy seeks to detect small patterns indicative of neurodegenerative diseases even in complicated and noisy medical data, such as retinal scans. Using probabilistic reasoning which follows hierarchical feature representations of the raw data the proposed technique classifies data when there is uncertainty. When used this method, standard CNN models surpass predicted accuracy, precision, recall, and F-measure. Regarding early diagnosis and tailored healthcare decision-making, the hybrid deep CNN probabilistic classifier is a real clinical wonder with an outstanding recall of 99%, precision of 98%, and accuracy of over 99%.
Keywords: Neurodegenerative Disorders, Hybrid Deep CNN Probabilistic Classifier, Early Prediction, Classification.

1. Introduction

Recent work has focused on the difficulties early ND detection by machine learning presents. Al-Hameed et al. (2019) developed an original artificial intelligence system for non-invasive early identification of neurodegenerative cognitive impairment. Bachli et al. (2020)

investigated neurocognitive biomarkers nationalistically using machine learning models in order to standardise and enhance the dependability of diagnostic techniques.In their study, Chudowicz et al. (2024) investigated the potential of digital biomarkers and machine learning for early diagnosis of neurodegenerative illnesses. Wearable sensors monitoring gait patterns may improve the accuracy of ND diagnosis, according to Erdaş et al. (2023).

In their 2024 study, Dhahi et al. assert that nanotechnology will form the foundation of future diagnostic technologies. The use of nanobiosensors to the search for biomarkers of neurodegenerative illnesses will be a major driver. García-Gutierrez et al. (2022) claim that genetic algorithms might improve the accuracy and speed of diagnosis.Torres et al. assessed robotic gaits in advance of their 2023 trial. Extreme gradient boosting, recurrent neural networks, and support vector machines are among the well-known machine learning methods for ND detection and categorisation. These techniques enable it to acquire data in addition to motion, sound, and handwriting. To improve the ND detection abilities of an AI system, Cincovic et al. (2024) used neural network changes and a modified metaheuristic approach.Senatore et al. (2019) addressed interpretability in AI-based diagnostics using evolutionary algorithms, therefore underlining the need of doctors' awareness of AI systems. Another approach might be to combine data from neuroimaging, behavioural, and genetic research. Several research aiming at enhancing diagnostic accuracy attempted to collect various types of data. Lima et al. (2022) and Mengarelli et al. (2022) are two examples of such studies. García-Gutierrez et al. (2022) use genetic algorithms to the diagnosis of frontotemporal dementia and Alzheimer's disease, therefore highlighting the potential of artificial intelligence in supporting difficult treatment choices.

Powerful artificial intelligence models will soon be able to identify neurodegenerative illnesses using imaging, medical history, genes, and biomarkers produced from other sources. According to Feng (2023) and Farid et al. (2020), artificial intelligence might help with early neurodegenerative disease detection as well as with the supply of tailored treatment options. Benefits of this developing field of research include increased accuracy, efficiency, and least invasiveness in neurodegenerative disease diagnosis and treatment. Tăuţan et al. (2021) mostly address model interpretability, ethical artificial intelligence use, and data quality assurance. Artificial intelligence will be able to completely profit from these hurdles eliminated in the diagnosis of clinical neurodegenerative illness.

2. Background Study

Al-Hameed, S., et al. (2019) these authors have several consequences. First, it is shown that a few recoverable acoustical properties are crucial in distinguishing Neurodegenerative Disorders (ND) from Functional Memory Disorder (FMD). Changes in neurobiology connected to a neurodegenerative cognitive disorder influence auditory output. Second, clinics and frequent clinical encounters readily execute the recommended technique. This will speed up the examinee's diagnosis and require less examiner effort. Notwithstanding the constraints of this study, their findings imply that acoustic-only characteristics provide a low-cost, straightforward substitute for more complicated features requiring automatic speech recognition, part-of-speech parsing, and speech understanding for stratification of cognitively disturbed patients.

Bachli, M. B., et al. (2020) these authors obtained a first-of-its-kind identification rate of bvFTD and AD patients across three countries by combining cognitive tests with quantitative neuroanatomical indicators. The rather high categorization rates (>0.91) were subsequently revealed using machine learning approaches. Two more foreign samples also verified their great generalisability (>0.91). Using these metrics on new, unknown data from several sources shows their consistency. Thus, although more research may be necessary, their findings lend credence to the idea that computer-based algorithms that include these criteria might be a useful, inexpensive, and supplemental tool for personalized diagnostic and treatment decisions.

Cincovic, J., et al. (2024) these authors addresses the challenging and urgent problem of neurodegenerative disease identification by means of developing artificial intelligence systems. Utilizing both attention-based RNNs and time series classification, together with statistical analysis utilizing the XGBoost approach, a real-world clinical dataset is used for the early identification of neurological illnesses. Because algorithms rely heavily on hyperparameter selection to achieve desired outcomes, metaheuristic algorithms are used for parameter adjustment and selection. In addition, this study proposes and employs a tweaked version of the recently released SCHO method for parameter selection throughout three iterations. The optimizer that was shown suggests potential pairings with RNN, attention-based RNN, and XGBoost, with the best-constructed models surpassing 90% accuracy for time-series classification and 80% on basic classifications.

Dabbaghi, K. G., et al. (2023) ultimately, the incorporation of artificial intelligence with medical sciences has ushered in a new age in healthcare; the study of neurodegenerative diseases especially benefits from these developments. Artificial intelligence (AI) could completely transform Alzheimer's disease (AD) diagnosis, prediction, and individualized treatment by sifting through mountains of medical data including medical images, genetic information, clinical records, electroencephalogram (EEG) signals, quantifiable proteins in cerebrospinal fluid (CSF), blood and urine, driving habits, and more. By means of early diagnosis, illness progression prediction, disease classification, identification of novel biomarkers and medications, and treatment plan personalization, artificial intelligence algorithms assist healthcare providers. Still, the possible advantages of artificial intelligence for medical sciences are really noteworthy, and in the next years AI will probably become more and more crucial in healthcare.

De Stefano, C., et al. (2019) these authors investigated handwriting analysis methods for early neurodegenerative disease diagnosis, monitoring, and tracking. These authors examined MCI, Alzheimer's, and Parkinson's. These authors also address outstanding field issues. Handwriting analysis aids in diagnosing and monitoring the aforementioned illnesses. Alzheimer's disease sufferers' handwriting lacks fine motion and spatial structural control, according to research. Instead, Parkinson's disease patients' handwriting is most typically micrographia, slower movements, and jerky. Handwriting-based approaches for ND diagnosis assistance have showed promise, but their full potential has yet to be explored. Protocol specification is an open issue needing additional investigation.

Erdaş, Ç. B., et al. (2023) Determining the severity of neurodegenerative illnesses is critical to diagnosis. Correct diagnosis and disease severity will assist patients get the right medicine dose, enhancing quality of life and pharmaceutical effectiveness. In order to determine the severity of all PD, HD, and ALS disorders, this research builds an AI-based decision support system that uses gait dynamics and data. Experts are better able to assess patients rationally and make informed judgments when they use this method. To address the issues, the one-dimensional convolutional neural network (CNN) method, the suggested system, and a number of pure machine learning techniques were used. To further enhance machine learning performance, ensemble approaches such as voting and stacking were also used. Neurodegenerative illnesses diagnosed and graded accurately, according to study.

Feng, T. (2023) Several categories, including genetic data, neuroimaging data, and clinical data, have shown promising applications of artificial intelligence in the diagnosis of neurodegenerative disorders. In addition, there are problems with data collecting and interpretation that need fixing before AI can be used to diagnose neurodegenerative disorders with any degree of reliability or validity. To enhance the precision of future neurodegenerative disease identification, one possible strategy is to combine several AI modalities, such as the data analysis methodologies already stated. Furthermore, cooperative efforts between biomedicine and artificial intelligence professionals will help to guarantee that AI application in neurodegenerative disease detection is successful and efficient.

Ghaderyan, P., & Beyrami, S. M. G. (2020) these authors proposed a gait symmetry-based automated method for clinical and inexpensive ALS, PD, and HD detection. These authors examined unique symmetric properties using the sparse NNLS coding classifier. A greater level of symmetry was seen in healthy persons compared to NDD patients, and distance-based characteristics were able to quantify inter-limb disparities. The accuracy and description of dynamic gait variability were both enhanced by DGSW. Data contamination was avoided by emphasizing relevant variations using the Chebyshev distance. The NNLS approach improved NDDs classification accuracy by outperforming the SVM classifier. These factors explained the recommended approach's high accuracy among the three NDD types.

Mengarelli, A., et al. (2022) NDD identification utilizing gait data and PSDTD characteristics was effective using time-dependent spectral features alone. They also seem to reveal crucial dynamics that influence gait stride timings. With a fresh perspective on binary classification problems, the suggested diagnostic pathways worked well for NDD detection in a multi-class framework. The results of the first strategy's single learning phase were somewhat better than those of the second; however this finding is not borne up by study. In both cases, robust classification requires tiny feature sets with no more than seven attributes. Automated detection of NDD gait patterns and clinical assessment of disease severity and progression are two real-world applications that might benefit from these features.

Table 1: Comparison table on Neurodegenerative Disorders

Authors & Year	Key Focus	Methods	Results/Findings
Torres, A. M. C., et al. (2023)	Gait parameters for medical diagnosis	Statistical analysis to select appropriate descriptors; energy and power spectral density from spatiotemporal signals	Best classification results: Fuzzy C-means (90.23%), LAMDA (96.66%), NN (97.0%)
Singh, G., et al. (2018)	Comparison of AD, PD, MCI, and SWEDD using brain imaging	Machine learning with MRI data; automatic detection of relevant brain areas	Important biomarkers detected for early-stage disease diagnosis; adaptable framework for clinical use
Shusharina, N., et al. (2023)	Early diagnostics and correction of neurodegenerative and depressive disorders	Review of research progress; need for high-quality, large datasets	Lack of quality data limits ML model development; call for standardized data collection and labeling

Senatore, R., et al. (2019)	Automatic Parkinson's disease diagnosis via handwritten shape analysis	Cartesian Genetic Programming (CGP) on static features	CGP outperformed other methods; revealed decision criteria for clinical validation
Sánchez-DelaCruz, E., et al. (2024)	Classification of PD and HD based on gait biomarkers	Automated model selection for gait classification	Achieved ~90% classification accuracy; emphasized model customization for specific biomedical applications
Nam Nguyen, Q. D., et al. (2020)	NDD gait classification using GF signal and MSE values	Differential transformation, SMOTE, sequential feature selection, KNN, SVM	High classification accuracy for NDD gait patterns; improved by data balancing and feature selection
Mengarelli, A., et al. (2022)	NDD gait recognition using spectral features	PSDTD and time-dependent spectral features for multi-class classification	Effective classification with small feature sets (<7 features); supports clinical evaluation of NDD severity and progression

3. Proposed Methodology

Automated retinal layer segmentation, together with classification and prediction models, provides a huge step forward in the early diagnosis and prognosis of neurodegenerative disorders like Alzheimer's and Parkinson's. In this work, we examine the problems and future possibilities in this rapidly growing subject, with a particular emphasis on the integration of sophisticated segmentation methods with classification and prediction models. We provide a new method for neurodegenerative disease classification and prediction using retinal imaging data and a hybrid Deep Convolutional Neural Network (CNN) probabilistic classifier. Combining the expressive ability of deep CNNs with probabilistic modelling in the hybrid architecture makes illness classification and prediction more strong and interpretable. Especially in the presence of noise and distortions, defining the exact boundaries between retinal layers presents a difficult task in automated retinal layer segmentation. To solve this difficulty, new, very efficient segmentation algorithms must be developed for complicated retinal anatomy and picture variability.

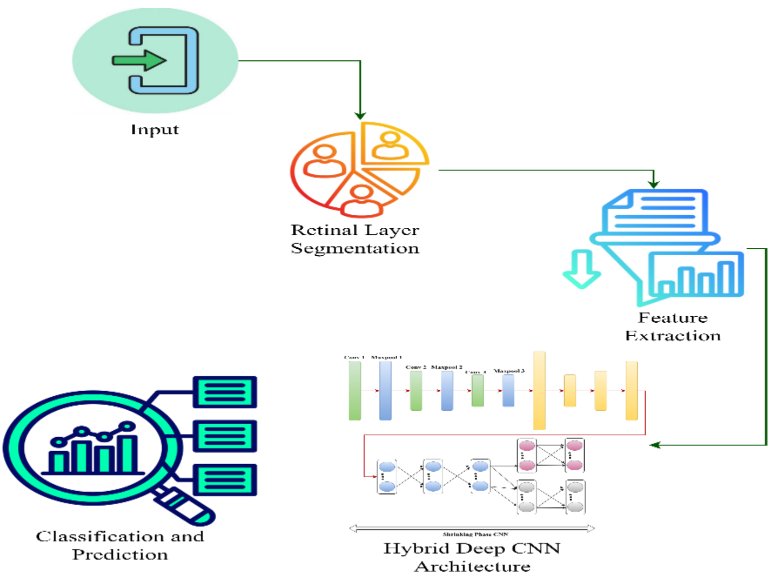

Figure 1: Overall Architecture

Figure 1 shows a method for analyzing retinal images using deep learning. The procedure begins with input and uses Retinal Layer Segmentation to divide important areas. Superiority some intriguing patterns emerge from the analysis of partitioned data. To control these variables and provide robust learning, a deep convolutional neural network (CNN) design incorporates fully connected and convolutional layers. In the end, the model aids in diagnosis and medical decision-making by searching for retinal illnesses utilizing categorization and prediction.

3.1 Hybrid Deep CNN Probabilistic Classifier

Probabilistic predictors of mixed deep convolutional neural networks (CNNs) are a potent machine learning tool for neurodegenerative illnesses. Retinal difficulties, Parkinson's disease, Alzheimer's disease, and other brain disorders may be found and tracked using this approach. By combining the feature extraction capabilities of deep CNNs, this model incorporates a probabilistic method that approximates prediction uncertainty, leading more accurate decision-making. Using the CNN component is common method for detecting minute patterns that signify neurodegenerative diseases. It extracts generalisable characteristics from complicated datasets such as imaging, EEG signals, and gait analysis. Analyzing these properties using a probabilistic classifier can help to account for data variability and uncertainty. Probabilistic classifiers include probabilistic graphical models and Bayesian networks. The hybrid approach relies less on human feature developers since deep CNNs can learn hierarchical features from raw data. Conversely, the probability predictor guarantees that the model can manage a broad spectrum of data and situations and still provide correct predictions each time. Combining the two techniques may help us to raise the guessing capacity of the system. This would therefore result in fresh approaches of diagnosis, classification, and illness prediction. Working with restricted or noisy medical data will especially benefit from this method as it models complicated linkages and dependencies within the data. Furthermore, the model adjusted to operate with other data modalities, so providing a flexible tool for early detection, diagnosis, and monitoring of neurodegenerative illnesses, so supporting doctors in customized healthcare decision-making. In clinical environments, where efficient therapy and intervention depend on quick and precise diagnosis of neurodegenerative disorders, such models have enormous potential.

$H_i = \mathrm{ReLU}\ (W_{conv} * x_i + b_{conv})$ ----------------- (1)

In a neural network, a convolutional layer operation is denoted as $\mathrm{ReLU}\ (W_{conv} * x_i + b_{conv})$. Here, x_i is the input feature at position x_i W_{conv}; b_{conv} is the bias term added to the outcome of the convolution. The convolution operation $W_{conv} * x_i$ produces a weighted sum of the input features, and then shifted by the bias W_{conv}. At last, the ReLU (Rectified Linear Unit) activation function is used to add non-linearity by zeroing all negative values and preserving positive ones thereby enabling the network to learn intricate patterns.

$H_{pooled} = \mathrm{MaxPool}(H_i)$ ----------------- (2)

$\mathrm{MaxPool}(H_i)$ denotes the operation of max pooling performed to the feature map H_iBy choosing the greatest value from every local area (or window) in the feature map, max pooling downsamples the input, thus preserving the most significant features such as edges or textures while so lowering the spatial dimensions. This offers some degree of translation invariance and helps to improve computing efficiency.

$a_{fc} = \mathrm{ReLU}(z_{fc})$ ----------------- (3)

The activation function used in the output of a fully connected (FC) layer of a neural network is $\mathrm{ReLU}(z_{fc})$. Here, z_{fc} is the raw output from the fully connected layer, calculated as a weighted sum of inputs plus a bias factor. To make z_{fc}hence non-linear and enable the network to mimic complex feature interactions, we set all negative values to zero while maintaining positive ones. Then, we apply the ReLU activation function.

$P(y = k|x_i) = \frac{\exp\,(W_{out} \cdot a_{fc} + b_{out})}{\sum_j (W_{out,j} \cdot a_{fc} + b_{out,j})}$ ----------------- (4)

With an input valuex_i, it computes the probability of a certain class $y\ = k$ by means of the weight and bias parameters for the output layer. The softmax function guarantees that all class probabilities total to 1 by normalizing the exponentiated outputs, hence enabling interpretability as probability.

$P(y_i|\emptyset(x_i))$ ----------------- (5)

Given a modified or processed input feature $\emptyset$, P y_i reflects the likelihood of the label y_i Here, $\emptyset(x_i)$ signifies a feature transformation or preprocessing function applied to the input x_i. This can include stages such feature extraction, encoding, or mapping. Usually in the framework of a probabilistic model or classification job, the equation implies that this modified input determines the probability *P* (y_i).

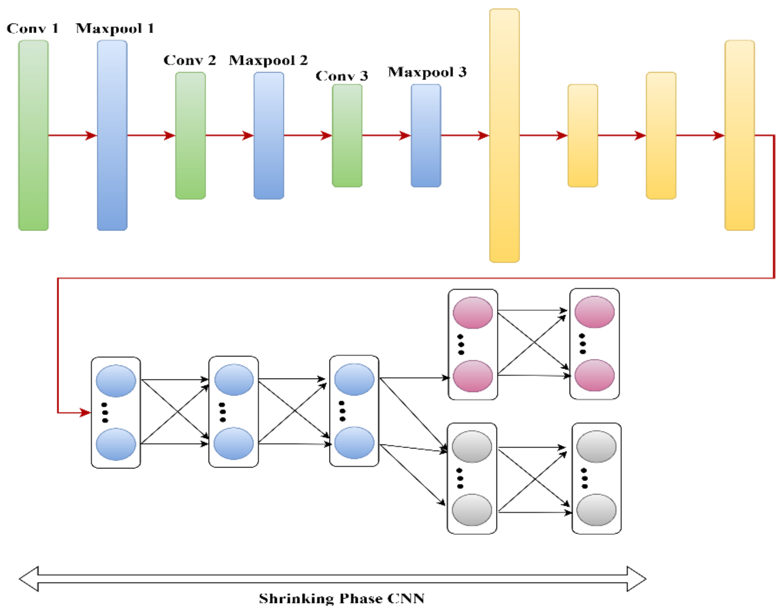

Figure 2: Hybrid Deep CNN Probabilistic Classifier architecture

With two primary components convolutional layers followed by a shrinking phase this Figure 2 shows a hybrid deep CNN architecture. The top part shows a succession of max-pooling (Max Pool) and convolutional (Conv) layers. Features are gradually removed and polished, hence lowering spatial dimensions while maintaining important patterns. These layers provide output that is sent to the lowest part, which is a Shrinking Phase CNN. This phase preserves discriminative information while using strongly coupled layers to lower feature dimensionality even further. Red arrows demonstrate how data moves across layers and aggregates into a complete feature representation for categorization or prediction.

Algorithm 1: Hybrid Deep CNN Probabilistic Classifier
Input: • Training dataset with input features (X) and corresponding class labels (y) • Parameters for the deep CNN architecture (e.g., number of layers, filter sizes, activation functions) Procedure: • Train the deep CNN architecture using the training dataset (X, y) to learn hierarchical feature representations from raw input data. This involves: o Convolutional layers for feature extraction o Pooling layers for dimensionality reduction o Fully connected layers for classification o Activation functions (e.g., ReLU, sigmoid) to introduce non-linearity o Loss function (e.g., cross-entropy loss) to measure the discrepancy between predicted and true class labels CNN Forward Pass: • Given an input sample xi, the forward pass through the deep CNN architecture computes the output of the final classification layer as: $y^{i} = \mathrm{softmax}(W_{out} \cdot \mathrm{ReLU}(W_{fc} \cdot \mathrm{flatten}(H_i) + b_{fc}) + b_{out})$ where: • H_i is the output feature map of the CNN for input x_i, • W_{fc} andb_{fc} are the weights and biases of the fully connected layer, • W_{out} and b_{out} are the weights and biases of the output layer, • ReLU is the rectified linear unit activation function, • flatten converts the 3D feature map into a 1D vector, • softmax Computes the class probabilities. □ Probabilistic Classifier: • The probabilistic classifier maps the extracted feature representations $\phi(x_i)$ to class probabilities $P(y_i \mid \phi(x_i))$ using a probabilistic model such as a Gaussian process or a

Bayesian neural network. The form of this mapping depends on the chosen probabilistic model and inference technique.

- Output:
- Trained hybrid model capable of probabilistic classification

Combining the best of deep CNNs for feature extraction with probabilistic models for robust classification, the hybrid deep CNN probabilistic classifier Feeding input data X and labels y into a CNN architecture comprising convolutional layers for hierarchical feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification, the training process generates Using a softmax activation function after modifications with weights, biases, and nonlinear activation (ReLU), the CNN generates class probabilities during the forward pass. After that, a probabilistic model such as a Gaussian process or Bayesian neural network which includes uncertainty into predictions maps the obtained characteristics to class probabilities. This hybrid method guarantees precise categorization and confidence estimations for every prediction.

4. Results and Discussion

The performance metrics are calculated in this result section. This result shows that the proposed methodology gives best performance comparing to the existing methodology.

4.1 Accuracy

In predictive modeling, accuracy is the measure of how close the model's projections are to real-world outcomes. Making predictions and judgments in a variety of circumstances relies on the model's reliability and accuracy, thus it assesses these characteristics.

T-True, F-False, P-Positive, N-Negative

$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$ ------- (6)

4.2 Precision

In predictive modeling, accuracy is the proportion of total expected positive observations to correctly forecasted positive observations. It displays how effectively the model lowers false positives, ensuring the genuine accuracy and reliability of the positive predictions it generates qualities necessary for decision-making and, as a result, error reduction in many other domains.

$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$ ------ (7)

4.3 Recall

Recall in predictive modeling is the fraction of real positive instances the model properly detected. In sectors like as medical diagnosis or fraud detection, identifying all positives is critical since it shows how well the model detects all relevant instances of a particular class.

$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$ ------ (8)

4.4 F-measure

The F-measure, which determines the harmonic mean of recall and accuracy, is a strong all-around measurement of how well a model is performing for models that need to prevent both false positives and false negatives.

$$\mathrm{F-measure} = 2 \times \frac{\mathrm{Precision} \times \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \text{ ------- } (5)$$

Table 2: Comparison table on Performance Metrics

Algorithms	Accuracy	Precision	Recall	F-measure
CNN	96	95	96	93
Deep CNN	97	96	97	94
Hybrid deep CNN	98	97	98	95
Hybrid Deep CNN Probabilistic Classifier	99	98	99	96

Table 2 performance measures show how well certain models perform in categorization problems. Strong accuracy and recall on CNN indicate that it can appropriately recognize a good amount of the data but with somewhat less precision. Reflecting a better balance between properly detecting positive cases and reducing false positives, the Deep CNN increases both accuracy and precision. Suggesting that the mix of many deep learning approaches improves model performance, the hybrid deep CNN obtains even better accuracy, precision, and recall. By using probabilistic approaches to improve decision-making, presumably resulting in more accurate predictions with less error in classification, the hybrid deep CNN with a probabilistic classifier further increases these metrics, notably precision and recall. The little rise in F-measure emphasizes how much model dependability and robustness have improved generally.

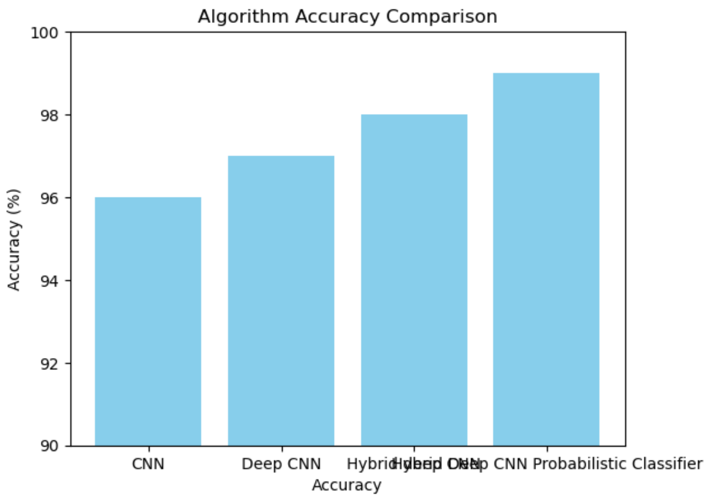

Figure 3: Comparison chart on Accuracy

The Figure 3 compares algorithm accuracies across several models, including CNN, Deep CNN, Hybrid Deep CNN, and Probabilistic Classifier. The CNN model has an accuracy of about 96%, while the Deep CNN model beats it somewhat, approaching 97%. The Hybrid Deep CNN achieves higher accuracy, topping 97%, demonstrating the value of merging architectures. The Probabilistic Classifier has the greatest accuracy, approaching 99%, demonstrating its better performance in the analyzed position. This evolution demonstrates the usefulness of advanced and hybrid techniques in improving classification results.

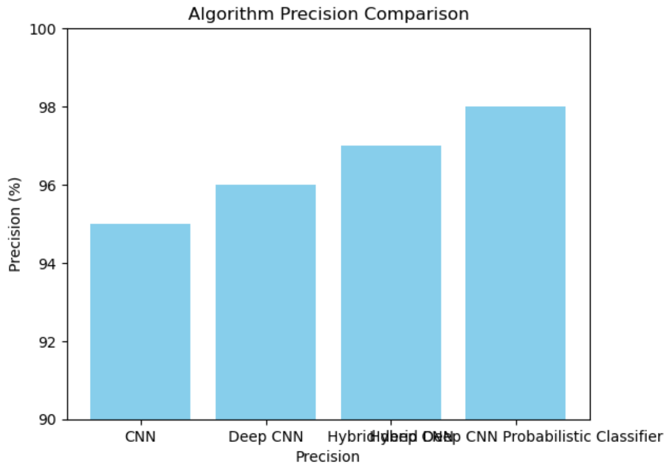

Figure 4: Comparison chart on Precision

Figure 4 compares algorithm precision across several models, such as CNN, Deep CNN, Hybrid Deep CNN, and Probabilistic Classifier. While the Deep CNN model surpasses the CNN model by almost 96%, its accuracy hovers around 95%. The Hybrid Deep CNN, which scored 97%, demonstrates the benefits of merging architectures by obtaining higher accuracy. The Probabilistic Classifier performs best in the studied position in terms of accuracy, approaching 98%. This work demonstrates how sophisticated and hybrid approaches may improve classification performance.

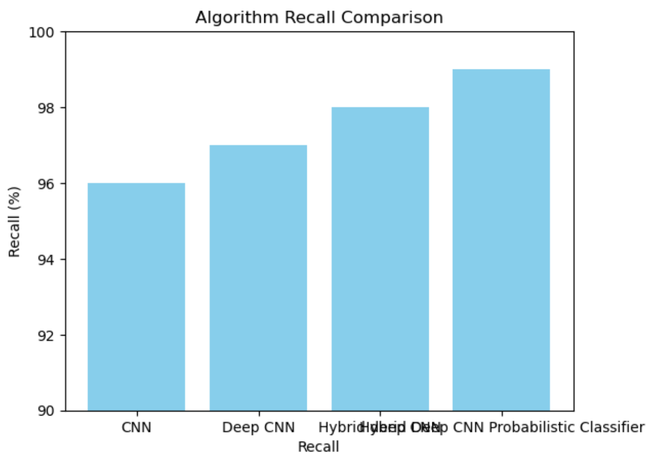

Figure 5: Comparison chart on Recall

Figure 5 shows one variant of the algorithm's recall. Along with this, there are probabilistic classifiers, Convolutional Neural Networks, Deep Convolutional Neural Networks, and hybrid Deep CNNs. In comparison to the CNN model's 96% Recall, the Deep CNN model achieves a much higher value of 97%.The 97% success rate of the Hybrid Deep CNN was attained by showing that mixing architectures may boost recall. In the tested situation, the Probabilistic Classifier achieved recall close to 99%, making it the best choice. According to the results of this research, utilizing complicated and hybrid approaches may improve classification performance.

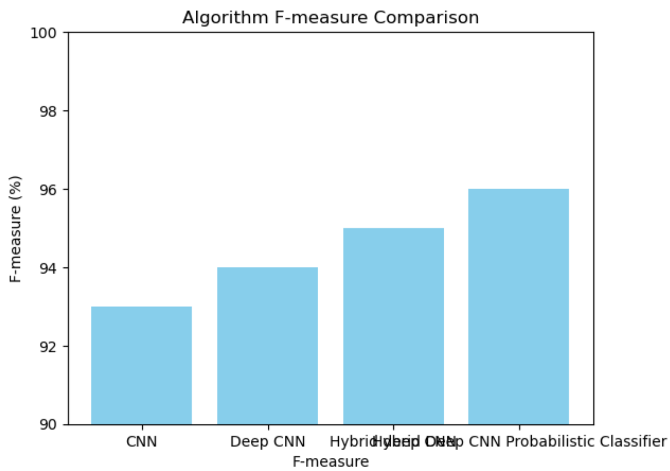

Figure 6: Comparison chart on F-measure

The method F-measure is compared in Figure 6 across many models: Probabilistic Classifier, CNN, Deep CNN, and Hybrid Deep CNN. With an F-measure of almost 93%, the CNN model does really well; the Deep CNN model scores about 94%. The Hybrid Deep CNN achieves a top F-measure of 95% thus demonstrating the value of merging architectures. Having an F-measure score of more than 96%, the Probabilistic Classifier beats all other choices under explored role. As this work demonstrates, sophisticated and hybrid strategies allow one to improve classification performance.

5. Conclusion

The proposed hybrid Deep CNN probabilistic classifier improved in identifying and categorizing neurodegenerative illnesses over standard CNN-based models. This method improves retinal imaging data and decision accuracy by estimating uncertainty using probabilistic models and deep learning. The hybrid model shows better than the independent CNN models for classification tasks including F-measure, accuracy, precision, and deep CNN. Probabilistic classifiers are ideal for medical applications where misclassification might have disastrous consequences since they can handle data uncertainty and dramatically improve models. The suggested method for the hopeful early diagnosis and progressive surveillance of neurodegenerative diseases has given clinicians a powerful and adaptable tool. The system is very adaptable to many clinical settings since it can manage noisy or otherwise constrained data and works with various forms of medical data. Future improvements to the model, including the addition of real-time forecasting components and multimodal data sources, will help to greatly increase its therapeutic potential. A key take away from this study is the potential for hybrid and probabilistic deep learning algorithms to revolutionize medical diagnostics and tailored therapy.

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