A Study on Brain Tumor and Parkinson's Disease Diagnosis and Detection using Deep Learning

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ABSTRACT

Consider the possibility that we live in an area far from a doctor, or that we may not have enough resources to pay the hospital cost, or that we may not have enough time to take off work. The use of advanced computers to diagnose diseases will be lifesaving in such situations. Scientists have developed a number of artificially intelligent diagnostic algorithms for illnesses such as cancer, lung disease and Parkinson's disease. Deep learning employs massive artificial neural network layers of interlinked nodes that can reorganize themselves in response to updated data. This approach enables machines to self-learn without the need for assistance from humans. The emphasis of this article is on current developments in machine learning that have had major effects on identification for the detection of a variety of illnesses, such as brain tumor segmentation. Human-assisted manual categorization may lead to erroneous prediction and diagnosis, thus one of the most important and a useful technique is brain tumor segmentation tasks in medical image processing that are difficult. Furthermore, it is a difficult challenge because there is a vast volume of data to assist. Since brain tumors have such a wide range of appearances and since tumor and normal tissues are so close, extracting tumor regions from photographs becomes difficult. The advancement of clinical decision systems of support necessitates the identification and recognition of the appropriate biomarkers in relation to specific health problems. It has been established that handwriting deficiency is proportionate to the severity of the situation of individuals' Parkinson's disease (PD).

Keywords: Artificial Intelligence, Artificial Neural Network, Computer Aided Diagnosis, Machine Learning, Segmentation.

1. INTRODUCTION

Supported by a computer in the medical sector, diagnosis is an increasingly increasing and diverse field of study. Latest advances in artificial intelligence computer learning offer increased disease perception and diagnostic precision. By learning and acquiring information, computers are given the capacity to reason. To differentiate data sets, machine learning techniques are employed that come in a variety of forms. [1,2]. They're controlled and unsupervised at the same time. Algorithms for deep learning, reinforcement semi-supervised, evolutionary has been studied and applied for better results [3].

Parkinson's disease (PD) is one of the most prevalent neurological illnesses in persons over 65 years old. Because this illness is progressive in nature, failure to diagnose it early and monitor it at various stages would have a substantial cost-cutting impact for patients in terms of healthcare as well as serious health-related problems. Instability, Rigidity in posture, bradykinesia and tremor are some of the symptoms of movement abnormalities that are often seen in Parkinson's disease patients at various stages. It is critical to identify PD at an early stage in order to avoid serious consequences for PD patients. Finding differences in handwriting and drawing skills is one of the most popular frequent impacts that are readily visible among PD patients and utilized most often in the early stages of diagnosis.

Noninvasive tests such as sketching a spiral, waves, and other handwritten texts may be used to distinguish between individuals who have and don't have Parkinson's disease [26, 27].

Parkinson's disease in its early stages, previous researchers and doctors discovered a link between spiral sketching and handwriting.

The main disadvantage of these types of diagnosis is that they need accurate interpretation of drawing and handwriting. Traditionally, drawings or handwritings were created on paper and physically translated by interpreters who were experts in certain fields. Now that digital technology is available, it is easier to do such tasks digitally, and machine assessments are more precise and accurate than in the past. Some of the common characteristics included in the drawings may be utilised as possible markers to distinguish between various groups of participants, such as healthy and PD patients, and those tasks could be used to conduct a real-time reliability study.

In recent years, the most prudent choice for recognizing anything in actual time has been to automate the system so that we can do the same task in less time and with more precision. In this regard, machine learning methods are more successful and have shown sufficient promise for application in real-world scenarios.

Supervised learning: It provides a compilation of instances in practice with appropriate goals, and algorithms answer based on some training set, all questions should be answered properly for possible inputs. Supervised Learning [4] is another term for learning from instances. Supervised Learning takes the form of classification and regression.

Unsupervised learning: The unsupervised learning approach attempts to identify correlations in the input data and then classifies the data depending on these similarities. Density estimate [5] is another name for this. Clustering is a feature of unsupervised learning that creates clusters based on similarities.

Semi-supervised learning: A supervised learning method that is partly supervised is a kind of supervised learning technique. Unlabeled data are often used for training (A tiny quantity of categorized data and a big number of unlabeled data are typical.) between unsupervised (unlabeled information) and supervised learning is semi-supervised learning (labeled-data) [6]

Reinforcement learning: Behaviorist psychology supports this reinforcement learning. If the answer is incorrect, an algorithm is notified, but it is not notified of how to correct it. It must investigate and test different options before it discovers the correct answers

[7]. Learning with a reviewer is another term for it. It makes no suggestions for change.

Evolutionary Learning: This human evolution learning may be compared to how biological organisms develop to improve their odds of surviving and generating children. [8] We may implement this model in a computer by using the notion of fitness to determine the accuracy of the response.

Deep learning: Back propagation is a method for learning all of the model parameters at the same time to optimize the task's performance [9]. It employs a deep graph of several processing layers comprised of a variety of nonlinear and linear transformations.

1.1. Machine Learning Techniques for Disease Diagnosis and Detection

The quantification of disease progression during medical care is possible thanks to the automatic and continuous measurement of biomarkers [10, 11]. Increased sensitivity and efficacy of medical therapies will aid in the implementation of more reliable disease management, which reduces the amount of participants required in clinical trials as well. This article analyses and compares several machine learning algorithms for detecting illnesses including cancer, lung disease, and Parkinson's disease.

2. DEEP LEARNING IN CANCER DETECTION

The gold standard for illness detection research is biological tissue extracts from pathologist's reports. One of the most common forms of breast cancer is cancerous tumors in the mass. Malignant tumors are difficult to identify on mammograms because they are concealed by different densities of parenchyma tissue structures.

Following the advent of deep learning, current advances in the field of machine intelligence have ushered in a paradigm shift across all industries. In the healthcare sector, the development of deep learning and sophisticated computer-aided detection systems has led to more precise and accurate diagnosis. When it comes to Parkinson's disease, there are a number of biomarkers that must be examined in order to determine a patient's clinical status. Hand tremors and dispersed motor flexibility in the hands are two of the most common symptoms of Parkinson's disease, and they contribute to a reduction in the capacity to draw and write. As a result, assessing the capacity to write and draw may be regarded a critical indicator for determining Parkinson's disease clinical development and diagnosis. This study investigates a technique for evaluating the sketching pattern of spirals and waves in Parkinson's disease patients, as well as identifying Parkinson's disease. The

system was built using two-dimensional convolutional neural networks and voting-ensemble classifiers.

Smita Jhajharia developed a model based on neural networks and principal component analysis for predicting breast cancer prognosis (PCA) features that has been processed. To apply a predictive model, a multivariate survey computational method was combined using a machine learning method based on artificial intelligence [12]. Principal component pre-processes data, analysis and chooses the most relevant characteristics for AI processing. For the classification of new cases, the ANN learns trends in the records. Experimental review reveals that the accuracy is 96 %. For mass detection in mammograms, Zheng L suggested a discrete wavelet transform (DWT) method that incorporates several artificial intelligence capabilities. Among the AI methods are dimension analysis of fractals, multi-resolution Markov random fields, and the dogs-and-rabbits algorithm. [13]. Dimensional examination of fractals is used as a pre-processor in mammography to assess the estimated positions of cancer-prone areas. The LL sub band of a three level DWT the mammogram's breakdown is segmented using the rabbits-and-dogs clustering algorithm. Finally, a tree-type classification technique is used to decide if a given area is cancer-prone. According to the verification data, the sensitivity of the suggested method is 97.4 % and an amount of false positives per picture of 3.91 %.

Table 1. Cancer identification methods based on machine learning

Techniques of Machine Learning	Publisher	Year	Disease	Accuracy
PCA, ANN	Smita Jhajharia	2016	Cancer	95.9%
Dogs-and-Rabbits algorithm, fractal dimension analysis, DWT, Markow random method	Zheng L	2014	Cancer	97.4%
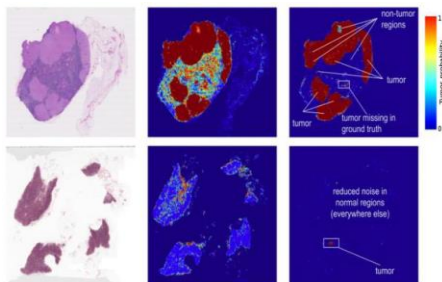
Figure 1 Deep learning diagnosis of tumor

One of the most difficult and time-consuming jobs is separating the region of interest from a person, and the challenge of isolating a MRI brain picture of a tumour is crucial. Researchers from all around the globe are working on determining the best-segmented ROI and simulating many alternative methods from diverse perspectives. The usage of Neural Network-based segmentation provides great results nowadays, and it is becoming more popular by the day.

The suggested approach has not been tested, and the following results have been obtained: a full segmentation procedure based on Mathematical Morphological Operations and a spatial FCM algorithm that saves time in computation; however, the suggested approach has not been tested, and the following results have been obtained: The classifier has an accuracy of 86.5 % and a specificity of 92% in detecting cancer is developed by Devkota *et al.* [14]. Yantao *et al.* [15] used a technique that was similar to the segmentation technique based on histogram. The brain tumor segmentation problem (tumor, necrosis, plus tumor, edoema, and normal tissue) using two modalities FLAIR and T1 is a three-class grouping question. To identify irregular regions, a region-based active contour model using FLAIR modality was employed. The k-means procedure was used to differentiate edoema and tumor tissues in unhealthy regions using the contrast enhancement T1 modality, with a sensitivity and Dice coefficient and of 90.2% and 73.5% respectively.

In terms of the number of true positives, the convolutional neural networks model for both wave and spiral drawings performed well. However, the original null hypothesis proposed that healthy individuals may be predicted as Parkinson's patients with minor misclassifications, while Parkinson's patients must not have a single misclassification. Due to the existence of stage 2 and 3 misclassification in spiral and wave for Parkinson's patients, CNN models did not agree with this specific hypothesis. As a result, a combinatory analysis was required, and we used the prediction probabilities of both the wave and spiral CNN models to train two separate classifiers in order to get an Ensemble judgement.

All pictures were treated to a static policy-based augmentation in order to prepare them for training. Because the dataset contains a very small number of pictures, using Deep Learning methods such as CNNs becomes problematic. As a result, picture augmentations were done to ingest some synthetic examples in the dataset for training as well as to enhance the dataset's variety. Tables 2 and 3 mentioned the different image augmentation parameters that were applied to the wave and spiral training data.

2.1. Preprocessing and augmentation of data

Resizing and histogram equalisation were applied to the pictures utilised in the research. The spiral drawings' pictures were scaled to 256 px wide and 256 px height, while the wave sketches were resized to 256 px width and 512 px height. The pictures gathered for the research show a lack of contrast and brightness, as well as general clarity. As a result, utilising Histogram equalisation, contrast augmentation and correction were applied to all of the pictures. All pictures were treated to a static policy-based augmentation in order to prepare them for training. Because the dataset contains a very small number of pictures, using Deep Learning methods such as CNNs becomes problematic. As a result, picture augmentations were done to ingest some synthetic examples in the training dataset as well as to enhance the dataset's variety.

Table 2. Data Augmentation Parameters for Spiral Sketches

Parameters for Augmentation	Settings
Horizontal Rotation	TRUE
Vertical Rotation	TRUE
Range of Width Shift	0.1
Range of Height Shift	0.1
Brightness Scale	0.5,1.5
Range of Shear	0.2
Range of Zoom	0.2
Max Crop Percentage	0.2
Crop Probability	0.3
Range of Rotation	360

Table 3. Data Augmentation Parameters for Wave Drawings

Parameters for Augmentation	Settings
Horizontal Rotation	TRUE
Vertical Rotation	TRUE
Range of Width Shift	0.1
Range of Height Shift	0.1
Brightness Scale	0.3,1.8
Range of Shear	0.2
Range of Zoom	0.2
Max Crop Percentage	0.3
Crop Probability	0.1
Range of Rotation	5

Badran *et al.* utilised a clever edge detection model combined with adaptive thresholding to eliminate the ROI utilizing edge detection methods. [16]. There were 102 images in the dataset. Images were first preprocessed, and then adaptive thresholding was applied to two different neural networks, the first of which used canny edge detection and the second of which used adaptive thresholding. The Harris technique identifies distinguishing elements from the segmented picture, which are then encoded as a level number. Then two neural networks are used, one for detecting whether the brain is stable or tumor-infested, and the other for determining the type of tumour. When comparing the two models and depicting the effects, the canny edge detection system performed better when it comes to precision. Pei *et al.* [17] suggested a strategy for improving Longitudinal MRI tumor segmentation based on texture by using tumor growth patterns as novel features. After removing textures (such as fractal and mBm) and intensity functions, label maps are worn to model tumor cell density prediction and growth. The model's output was measured using the Mean DSC with density of tumors cells of LOO: 0.819301 and 3-Folder: 0.82121.

Dina *et al.* [18] proposed a Learning Vector Quantization algorithm centered on the architecture of Probabilistic Neural Networks. A total of 64 MRI scans were used to test the model, the test set consisted of 18 individuals, whereas the training set consisted of the remaining individuals. The photographs were smoothed with the Gaussian filter. The updated PNN system slashed 79 % of the loading time. Principal Component Analysis (PCA) was used by Othman *et al.* to develop a probabilistic neural network-based segmentation method to remove characteristics and reduce the data's high dimensionality. [19]. The MRI images are transformed to matrices, which are then, classified using a Probabilistic Neural Network. Finally, a performance evaluation is carried out. There were 20 subjects in the training dataset and 15 in the evaluation dataset. The precision varied from 73% to 100% depending on the spread value. Rajendran *et al.* [20] used an Based on Region based Fuzzy Clustering and deformable model, we used an enhanced Probabilistic Fuzzy C-Means method with specific morphological procedures to obtain 95.29 % and 82.09 % ASM and Jaccard Index. For tumour segmentation, Zahra *et al.* [21] used the LinkNet network. They started by sending all seven training datasets to a single Linknet network for segmentation. They ignored the photos' view angle and developed a way for Without the requirement for preprocessing, the most prevalent kinds of brain tumours may be automatically segmented by CNN. A single network receives a Dice score of 0.72 and for various systems, 0.78 is received. The methods for segmenting tumors from a 2D Brain MRI are presented, as well as a comparison of our proposed machine learning and deep learning classification models. With SVM, they achieved 92.41 % accuracy, and with CNN, they achieved 97.86 % accuracy.

Table 4. Performance of the CNN Model

| Sr. No.	Training Image	Testing Image	Precision (%)	Portion Ratio
1	152	65	92.97%	70:30
2	174	43	97.86%	80:20

3. DETECTION OF LUNG DISEASES USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence (AI) is being handed down to increase the precision of lung disease diagnosis. Machine learning makes use of algorithms that can learn from and analyse data in order to make predictions. For detecting CVDs, Juan Wang proposed a deep learning algorithm. To make the distinction, a 12-layer convolutional neural network was utilized BAC (breast arterial calcifications) from non-BAC and to diagnose BAC using a pixel-by-pixel, patch-based technique. Both the calcium mass quantification analysis and free-response receiver operating characteristic (FROC) analysis were used to evaluate the system's performance [22]. The deep learning method, according to the FROC research, reaches detection speeds similar to human specialists. The calculated calcium mass is close to the ground truth, according to the calcium mass quantification study, with a linear regression between them yielding a coefficient of determination of 96.23 %.

Shubhangi Khobragade suggested an algorithm for detecting lung illnesses that are severe automatically. For the diagnosis of lung diseases such as tuberculosis, lung cancer, and pneumonia, artificial neural network technique is used to segment the lungs, remove lung features, and classify them [23]. The intensity-based technique and the technique based on discontinuity are utilized to identify lung limitations. Geometrical and Statistical characteristics may be calculated. To identify pictures, feed forward and back propagation techniques are employed. It was found that the accuracy was 86% [28-30].

Table 5. Machine Learning Techniques for Detecting Lung Disorders Automatically

Machine Learning Techniques	Author	Year	Disease	Accuracy
FROC, ANN	Jun Wang	2017	Lung Disease	96.24%
Feed Forward and Back Propagation Neural Network	Shubhangi Khobragade	2017	Lung Disease	86%
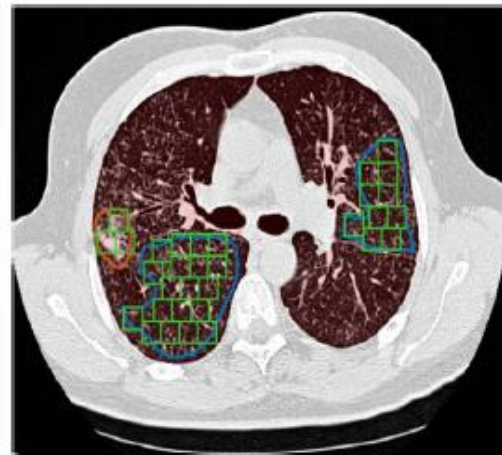
Figure 2 Annotations on a CT slice are used to generate image patches in this example.

Transparent red is used to show the lung area. Polygons are used to depict pathology areas in the real world. The patches have a 100% overlap with the lung, at least an 80 percent overlap with reality, and no overlap with each other.

## 4. TECHNIQUES FOR MACHINE LEARNING IN PARKINSON'S DISEASE

Parkinson's Parkinson's disease (PD) is a neurodegenerative disorder that impairs movement. The multistage classifier developed by Satyabrata Aich, Sabyasachi Chakraborty, Eunyoung Han, Jong-Seong-Sim, , Jinse Park, and Hee-Cheol Kim used deep learning algorithms and convolutional neural networks to identify Parkinson's disease from Wave and Spiral Sketches and produced promising results. The study's model's performance, average memory, average precision, and average f1 score were 93.3 %, 94 %, 93.5 %, and 93.93 %, respectively. Furthermore, to test the model's generalizability, a 5-fold cross validation was performed on the entire dataset, and it was discovered that the model generalised well between the two groups and also displayed a consistent bias toward precision and recall across random data folds of preparation, validation, and research. In the study dataset, there were 30 pictures of wave sketches and 30 images of spiral sketches. In addition, we can see from the uncertainty matrix that there are two missorted in the Healthy class, all of which were predicted to be Parkinson's disease. They have gone through a thorough examination of the possibilities of those two misclassified samples, it was discovered that the sketches made by some human specimens were deformed and very similar to the drawings created by Parkinson's sufferers. As a consequence, since all of the healthy patients were matched to the same age group, it's likely that a stable

individual living with Parkinson's disease may be a victim of progression.

Using Multilayer Perceptron, BayesNet, Random Forest, and Boosted Logistic Regression, Kamal Nayan Reddy Challa, Venkata Sasank Pagolu, Babita Majhi and Ganapati Panda created automatic diagnostic models [24]. The highest result was found to be Boosted Logistic Regression, which had an excellent precision of 97.159 % and a 98.9 % region according to the ROC curve.

Sachin Shetty and Y. S. Rao proposed an SVM-based machine learning approach to identify Parkinson's disease based on gait analysis [25]. The Support vector machine (SVM) classifier built on a Gaussian radial basis function kernel achieves an overall precision of 83.33 %, a strong identification rate for Parkinson's disease of 74.99 %, and poor false positive findings of 16.66 % [36-40].

The model's performance, as seen in the graph, is completely consistent with the hypothesis that was originally proposed. In addition, the confusion matrix reveals two misclassifications in the Healthy category, both of which were anticipated to have Parkinson's disease. Now, after carefully examining the probability of those two misclassified samples, it was discovered that the sketches produced by those specific individuals were very deformed, and that they were quite comparable to the drawings made by Parkinson's sufferers. As a result, it's possible that a healthy individual who is diagnosed with Parkinson's disease may be a subject of progression, since all of the healthy subjects were matched to the same age group.
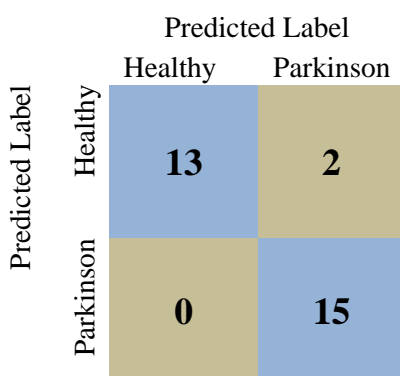
Figure 3 Confusion Matrix

Principal component analysis, rotation forest ensemble using support vector machines, and sparse multinomial logistic regression, and artificial neural networks, and boosting methods are among the rigorous methods suggested by Indrajit Mandal and N. Sairam for treating Parkinson's disease (PD) [40]. For related feature collection and rating, a current ensemble approach as a classifier, a Bayesian network optimised

using the Tabu search method is employed, together with Haar wavelets as a projection filter. Sparse multinomial logistic regression and Linear logistic regression have the greatest accuracy of 100 % and sensitivity, specificity, and sensitivity, specificity, respectively of 0.995 and 0.983. The results are established using adjusted t-tests in both investigations, which have 98.98% and 94.99% confidence levels [31-35].

Table 6. Machine Learning Techniques for Parkinson's Disorder Predictive Diagnosis

Machine Learning Techniques	Author	Year	Disease	Accuracy
Boosted Logistic Regression	Kamal Nayan Reddy Challa	2016	Parkinson Disease	97.15%
SVM using a Gaussian radial basis function kernel	Sachin Shetty Y. S. Rao	2016	Parkinson Disease	83.33%
Linear LR NN SVM SMO Pegasos AdaBoost Additive L R Ensemble Selection FURIA Multinominal Ridge LR RF Bayesian LR	Indrajit Mandal N. Sairam	2012	Parkinson Disease	96.58% 96.05% 96.58% 95.22% 96.58% 96.41% 96.75% 95.9% 96.41% 95.73% 96.07% 95.9%

5. CONCLUSION

This article provides an overview of current AI systems that may be used to forecast and diagnose different illnesses. The machine examines specific diagnostic imagery and related point data to generate a conclusion that can assist a doctor in making a professional decision. The Deep Learning system merely serves as a conduit for clinical image flow and archived image evidence. To use the Deep Learning framework, no application-specific engineering is needed. The use of Deep Learning algorithms to diagnose different diseases will speed up decision-making and reduce false-positive rates. The research explicitly shows that different Deep Learning algorithms improve the precision of disease detection for a variety of diseases.

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