1. Introduction

The field of health information systems and diagnosis has been gaining the interest of contemporary research because of the importance of its role in the early identification and recognition of different diseases. Parkinson’s Disease (PD) is a progressive neurodegenerative disorder influenced by the loss in production of dopamine in the substantia nigra that mainly results in the loss of mobility and motor control [1]. It is commonly associated with four cardinal movement disorders, specifically tremor, rigidity, bradykinesia, and postural instability. With this, the risk that PD imposes relies heavily on its early diagnosis because of the unpredictability and slow progression of its symptoms in nature. Normally, people being diagnosed with Parkinson’s Disease ranges from the late 55 to 75 years old, posing mild to severe mobility threats in consideration of their age.

Statistics show during the 5th Asian and Oceanian Parkinson’s Disease and Movement Disorder Congress that there is an increasing number of patients in the Philippines being diagnosed with PD accumulating to a total of 120,000 cases. This increase in prevalence of PD cases highlights several healthcare gaps in terms of the method of diagnosis of PD in the country. Currently, there is a limited and non-standard diagnostic test for PD. Researchers and medical experts are looking into different biomedical markers that may help with the diagnosis of the disease. One of which is human voice which is found to be an essential biomarker because of the factor of vocal impairment that appears to be one of the symptoms that 90 percent of the patient experiences. This paper highlights the human voice of 31 patients, 23 of which are diagnosed with PD, as an essential biomedical marker that aims to predict and diagnose PD through the utilization of an Artificial Neural Network.
2. Emerging Studies on Parkinson’s Disease and Biomarkers
The emergence in the relevance of the study has paved its way to various research and published papers. This section further discusses the vital findings related to the study.

A multi variant stacked autoencoder is often used in diagnosis because of its ability to predict and analyze more about Parkinson’s Disease symptoms than other existing systems [2]. Stacked autoencoder is one technique under the artificial neural network which is used for its effectiveness in coding the input data features. It undergoes a process of stacking data features and provides analysis for the decision-making system in the data prediction. In addition to this, the multi variant stacked autoencoder provides a more accurate PD detection and optimal treatment assistanship. In conclusion, upon comparing their work with other techniques, it showed promising improvements than other existing systems because of the multiple stacks of stacked autoencoders and its effective learning approaches [2].

Another research focuses on the use of a decision tree-based classifier in identifying or differentiating between the group of people who have Parkinson’s Disease and the other group of people who are healthy [3]. The study has used Max’s dataset from Oxford University with the collaboration of the National Centre for Voice and Speech, Denver, Colorado where the speech signals were recorded. Principal Component Analysis algorithm was used for the feature sets mainly because it compresses the data and the extraction of information [3]. Overall, a non-linear based classification approach was used and yielded an accuracy of 96.83% using random forest classifiers through PCA based feature sets. Relative to the previously discussed study, one article focuses on the use of speech signals in implementing morphological neural networks in identifying Parkinson’s Disease. This study used datasets from the “Oxford’s Parkinson’s Disease Screening” that contains 195 voice recordings of which 24 patients have Parkinson’s Disease [4]. They used dendrite morphological neural networks to identify the subjects with Parkinson’s Disease. An accuracy of 94.74% was obtained through using the stochastic gradient descent learning [4].

3. Artificial Intelligence and Neural Networks
It is in the biological nature of humans that seeks to understand the different phenomena that constitute around and within them. This curiosity to find the answers and explanations to human life has paved key advancements which remains to be pivotal in understanding different works of life. Developed in the 1950s, the study on Artificial Neural Network (ANN) aims to simulate a network of neurons through a working algorithm that is designed for computers to analyse and interpret practical applications in a humanlike manner [5]. The foundation of ANN is found through the arrangement of nodes, which mimics the relationship between neurons, in an interconnected manner.

![Artificial Neural Network Topology](image)

**Figure 1. Artificial Neural Network Topology**

The architecture of ANN heavily depends on the relationship of its network topology and the regulations set on its learning specifics [6]. Generally, nodes are interconnected in a one-dimensional pattern, also known as layers. Nodes are essential components of the ANN network because they contain
vital information that is processed by the algorithm [7] [8] [9]. The Input layer is structured to receive raw information of the data that will be processed and learned in the network. Each node in this layer receives multiple information associated with weighted values which initializes the learning specifics of the algorithm which will soon be optimized through the number of iterations that it will undergo. After which each node exceeds its certain threshold value, data will be transferred and processed in the so-called hidden layer. The hidden layer functions as the processing layer for all mathematical and conditional operations provided by the algorithm. A feedforward network is a single layer perceptron network which is static in nature and involves a one-way connection between the nodes of the layers [7]. Feedforward is an essential component for the backpropagation process of the learning specific because it enables the training data set to minimize the weight of the number of errors found within for the overall accuracy of the data.

4. Methodology

Multi Layer Perceptron Neural Network, a feed forward neural network, is the artificial neural network that is used in this study. This was implemented using the library from scikit learn and was provided through Jupyter lab using Python as the programming language. This will be further discussed in the next section of the paper.

The process flow of this study undergoes five main parts namely the voice measurement, feature selection and extraction, standard scaler, multi-layer perceptron neural network, and the prediction and diagnosis of classes whether a patient is healthy or is suffering Parkinson’s Disease. The standard scaler, multi-layer perceptron neural network, and the prediction and diagnosis of classes will be discussed in the following sections of the paper.

Figure 2. Methodology Process Flow Diagram

The voice measurement section discusses the dataset utilized in the paper. The paper examines a dataset retrieved from the UCI Machine Learning Repository by Max Little of the University of Oxford in partnership with the National Centre for Voice and Speech in Denver, Colorado. Because of the limited number of prevalent data of Parkinson’s Disease diagnosis, using biomedical voice
measurements, in the Philippines, the paper makes use of this dataset. In addition, this dataset uses pre-processed voice measurements as biomarkers in diagnosing Parkinson’s Disease which is essential to the study. The study uses 195 voice recordings from the subjects; 23 of which were affected by Parkinson disease while 8 were healthy in condition. In terms of the age, it varied from 33 to 87 years for those who are affected with the disease, while for the healthy people, it ranges from 41 to 82 years old. 44.1 was the frequency response during data gathering. Each column of the data file corresponds to an individual voice recording and contains certain attributes and features of the voice recording which will be used in the machine learning algorithm.

The feature selection and extraction section involves 17 attributes from the pre-processed voice measurements, as shown in Table 1. Each attribute contributes to the overall relevance of running the program. To provide further analysis and in-depth discussion about the chosen parameters, the following is explained alongside its relevance and importance to the study.

Multi-Dimensional Voice Program software (MDVP) is used to calculate acoustic parameters from a single voice sample [10]. Noise-to-Harmonic Ratio (NHR) which is used to measure the hoarseness of a person [11]. While, on the other hand, Harmonics-to-Noise (HNR) ratio measures the additive noise on the recorded voice signal [12]. The Recurrence Period Density Entropy (RPDE) uses the kind of attribute that “quantifies the extent to which dynamics in the reconstructed phase space after time delay embedding can be considered as strictly periodic, that is, repeating exactly” [13]. D2 is a correlation dimension. This computes for the recreation of the nonlinear dynamical phase space that generates the speech signal [13]. Detrended Fluctuation Analysis (DFA) measures the range of the “stochastic self-similarity of the noise in the speech signal.” [13]. Lastly, Pitch Period Entropy (PPE) is a variation acquired by getting the entropy of the probability distribution of the relative half-tone alteration. In getting the said distribution, one must acquire a pattern of pitch from the recorded vocals which will be converted into a logarithmic half-tone measure which will be then created into a “discrete probability distribution of half-tone alteration” [14].

| Attributes | Description |
|------------|-------------|
| MDVP:Fo(Hz) | Average vocal fundamental frequency |
| MDVP:Fhi(Hz) | Maximum vocal fundamental frequency |
| MDVP:Flo(Hz) | Minimum vocal fundamental frequency |
| MDVP:Jitter(%) | Several measures of variation in fundamental frequency |
| MDVP:Jitter(Abs) | |
| MDVP:RAP | |
| MDVP:PPQ | |
| Jitter:DDP | |
| NHR | Two measures of ratio of noise to tonal components in the voice |
| HNR | |
| RPDE | Two nonlinear dynamical complexity measures |
| D2 | |
| DFA | Signal fractal scaling exponent |
| spread1 | Three nonlinear measures of fundamental frequency variation |
| spread2 | |
| PPE | |
5. Multilayer Perceptron Neural Network

One classification of the Artificial Neural Network is the Multilayer Perceptron or MLP. The number of input neurons corresponds to the number of attributes the given dataset has (excluding the unimportant attribute which is the name column) which is 22. The number of hidden neurons ranges from 3 to 5 because of the data’s large features. Increasing the number of hidden neurons will have complications to the model and may possibly lead to overfitting. The number of output neurons is 1 because of the dataset being a binary classification.

![Multilayer Perceptron Network Diagram](image)

**Figure 3. Multilayer Perceptron**

The tests were performed in Jupyter lab using python as the main programming language for our study. We used scikit-learn MLP classifier in predicting and classifying the given dataset. The dataset was randomly split into train and test sizes having 70% and 30% respectively. The train size should have a higher percentage than the test size to provide better accuracy when it comes to predicting the model. Having a higher test size proportion will result in having a more accurate error estimate. There are only two classes in this dataset thus being a binary classification. The computation used for this in scikit learn is shown in equation (1) which is a logistic function or a sigmoid function [15]. The variable \( e \) represents Euler’s number while \( z \) is a statistical variable used for logistic mapping of the predicted values to probabilities. Also, this is to obtain the predicted output values between 0 and 1 being non-PD or PD, respectively.

\[
g(z) = \frac{1}{1 + e^{-z}}
\]

(1)

We used stochastic gradient descent as the solver for the weight optimization of our network. Stochastic gradient descent randomly picks a data point from the dataset and gradually, per iteration, moves down until it reaches the lowest point. This optimization method will help in minimizing the errors and reduce computational time. Moreover, the learning rate used is constant to ensure that the algorithm will have reduced training errors. As for the activation function for the hidden layer, we used \textit{relu} which stands for rectified unit function where it returns using equation (2) where \( x \) is the number of inputs to a neuron.

\[
g(x) = \max(0, x)
\]
The time complexity in backpropagation can be seen in equation (3). Where \( n \) is the number of training samples, \( m \) is the number of features, \( k \) is the hidden layers, \( h \) being the number of neurons, and \( i \) for the number of iterations made. Time complexity is the amount of time it takes to run the network [15].

\[
f(x) = \begin{cases} 0, & x > 0 \\ x, & x \geq 0 \end{cases}
\]

(2)

6. Results and Discussion
With the MLP Neural Network as the primary algorithm for classifying and predicting the test subjects between healthy and with Parkinson’s Disease, it has yielded an average accuracy of 91.5% from the comparison of the test data to the prediction output. Table 2 shows the confusion matrix of the program. Since the program uses a 70:30 ratio, with 30 being the test size, 59 voice recordings were randomly examined. From the confusion matrix, 11 are true positive and 43 are true negative.

|                  | Healthy | Parkinson’s Disease |
|------------------|---------|---------------------|
| Healthy          | 11      | 4                   |
| Parkinson’s Disease | 1  | 43                 |

From the data gathered in Table 3, precision received from classifying Healthy subjects was 92% while its f1-score was 81%. On the other hand, a 91% precision was obtained from classifying subjects that have Parkinson’s Disease while receiving a 95% f1-score. Recall is the ability of the classifier to find all the positive instances. The f1-score balances the precision and recall of the said classification. Support is the number of instances of a class in each dataset. As seen, the number of supports of Parkinson’s Disease is visibly higher than the number of supports found with the Healthy patients, this is because the given dataset is imbalanced in terms of the number of people involved. As stated in the earlier part of the paper, there are a total of 31 patients, 23 of which are diagnosed with Parkinson’s Disease. This imbalance is the primary reason for the difference in the number of supports.

|                  | Precision | Recall | f1-score | support |
|------------------|-----------|--------|----------|---------|
| Healthy          | 92%       | 73%    | 81%      | 15      |
| Parkinson's Disease | 91%  | 98%    | 95%      | 44      |
| Accuracy         | -         | -      | 92%      | 59      |
| Macro Avg.       | 92%       | 86%    | 88%      | 59      |
| Weighted Avg.    | 92%       | 92%    | 91%      | 59      |
The output instances of the confusion matrix were rechecked through comparing the output of the test data and the output predictions using Excel Sheets. Doing this additional step provides a more detailed explanation of the classification based on the given rows or instances of the dataset. As seen on Figure 4, the MLP classifier line graph shows little difference between the test_labels and the predicted output. This suggests that the implementation of the code design for the MLP classifier in predicting the output is a success.

![Figure 4. Test_labels vs. Prediction Graph](image)

The accuracy yielded from this study can be compared to other existing studies that use similar datasets. These existing studies used different types of neural networks in implementing the dataset. Such existing study is the use of Dendrite Morphological Neural Network. It has achieved a 94.74% accuracy in predicting or identifying subjects with Parkinson’s Disease [4]. Thus, comparing the accuracy obtained in this study to other existing studies can be considered as a way to further expand the possibilities of having different algorithms in the diagnosis and classification of disease with having accuracies greater than 90%.

7. Conclusion and Recommendations

Through the study conducted, the paper has met its objectives of implementing a Neural Network using Multilayer Perceptron Neural Network in classifying the Parkinson’s Disease dataset. It can be concluded that the use of the Neural Network will greatly impact the foundation of medical sciences and research on detecting patients with Parkinson’s Disease and other diseases. It is with the advancement of technology that different biomedical biomarkers, such as the human voice, have paved its way in the healthcare system and diagnosis. With the given results averaging an accuracy of 91.5%, the group can also show that the accuracies of other related studies are of that closer to the accuracy the group has achieved. Further recommendations for future works would involve the application of the study to other artificial intelligence network algorithms.

Acknowledgments

The authors highly appreciate the Office of the Vice Chancellor for Research and Innovation (VCRI) of De La Salle University, Manila for the conference publication support, and Gokongwei College of Engineering (GCOE) for providing an avenue for the researchers in the conduct of this research study.

References

[1] Jankovic J 2008 Parkinson's disease: Clinical features and diagnosis, *Journal of Neurology, Neurosurgery, and Psychiatry* **79** 368–376.

[2] Nagasubramanian G, Sankayya M, Al-Turjman F and Tsaramiris G 2020 Parkinson Data Analysis and Prediction System Using Multi-Variant Stacked AutoEncoder, *IEEE Access*, **8** 127004-127013.
[3] Aich S, Younga K, Hui K L, Al-Absi A A and Sain M 2018 A nonlinear decision tree-based classification approach to predict the Parkinson’s disease using different feature sets of voice data, *International Conference on Advanced Communication Technology (ICACT)* 638-642.

[4] Gutierrez-Loaiza L D and Alfonso-Morales W 2020 Morphological Neural Networks for Parkinson Detection through Speech Signals, *IEEE Colombian Conference on Applications of Computational Intelligence (IEEE ColCICI 2020)* 1-6.

[5] Bielby J, Kuhn S, Colreavy-Donnelly S, Caraffini F, O’Connor S and Anastassi Z A 2020 Identifying Parkinson’s Disease Through the Classification of Audio Recording Data, *IEEE Congress on Evolutionary Computation (CEC)* 1-7.

[6] Krogh A 2008 What are artificial neural networks?, *National Biotechnology* 26 2 195-7.

[7] Wu H, Zhou Y, Luo Q, and Basset M A 2016, Training Feedforward Neural Networks Using Symbiotic Organisms Search Algorithm, *Computational Intelligence and Neuroscience*, 2016 9063065 14.

[8] Billones R K C et al. 2015 Speech-controlled human-computer interface for audio-visual breast self-examination guidance system, 2015 *International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2015 1-6.

[9] Billones R K C and Dadios E P 2014, Hiligaynon language 5-word vocabulary speech recognition using Mel frequency cepstrum coefficients and genetic algorithm, 2014 *International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, Palawan, Philippines, 2014 1-6.

[10] Ray D Kent, Houri K Vorperian, Joseph R Duffy 1999, Reliability of the Multi-Dimensional Voice Program for the Analysis of Voice Samples of Subjects With Dysarthria, *American Journal of Speech-Language Pathology*, 8 2 129–136.

[11] Jotz, G P, Cervantes O, Abrahão M, Settanni F A P and de Angelis E C 2002, Noise-to-Harmonics Ratio as an Acoustic Measure of Voice Disorders in Boys, *Journal of Voice*, 16 1 28–31.

[12] Yumoto E 1982, Harmonics-to-noise ratio as an index of the degree of hoarseness, *The Journal of the Acoustical Society of America*, 71 6 1544-9.

[13] Little M A, Mc Sharry P E, Hunter E J, Spielman J and Ramig L O, 2009 Suitability of Dysphonia Measurements for Telemonitoring of Parkinson's Disease, *IEEE Trans Biomed Eng.* 56 4 1015–1022.

[14] Ozkan H, 2016 A Comparison of Classification Methods for Telediagnosis of Parkinson’s Disease, *Entropy*, 18 4 115.

[15] Rumelhart D E, Hinton G E and Williams R J 1986 Learning representations by back-propagating errors, *Letters to Nature*, 323 533–536.