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Research Article

The Development of an IoT-based Cyber-Physical System for Parkinson's Disease Patients Using ML Prediction Algorithm

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Abstract : Most people in the present eternal world are stressed and wrecked with diseases because of genetic, environmental, and emotional factors. Some of these diseases are incurable but different hopeful and life-extending treatment methods have been developed. An example is Parkinson's which causes degeneration in the brain and spinal cord with the most noticeable signs identified to be trembling, stiffness, slowness of movement, and difficulty in walking. Dementia is a form of brain condition symptomized by depression and anxiety that worsens as a result of Parkinson's and also makes it hard for the affected individuals to sleep at night. However, the prototypes of the treatment methods are hypothesized to limit the capacities of people with this disease. There is also a lack of diagnostic instruments to determine the precise status of some diseases, leading to the development of wearable sensors to diagnose Parkinson's disease (PD) in its earliest stages when treatment is most effective. In this work we propose a prototype to detect brain waves and other forms of human records through the installation of some effective sensors to determine the improvement in the central nervous system for the patients. A machine learning with prediction algorithm was adopted to observe the progress of the patients as well as to store the data in the cloud automatically to ensure reliable analysis of performance at any period. Furthermore, the prediction system is developed based on the fuzzy k-nearest neighbor (FKNN) for better classification. The proposed prototype is expected to assist in monitoring the patients in several ways other than just measuring vitals such as heart rate, blood pressure, and temperature.

Keywords : Parkinson's disease, Fuzzy k-nearest neighbor, Sensors, Cloud platform.

1 Introduction

Embedded systems are very important in the design of different electronic devices due to the ease of onboarding in microcontrollers and the primary role in prototypes. It has also been stated that 98% of all microprocessors are normally used in embedded systems. Moreover, the advancement of Internet of Things (IoT) and subsequent integration into cyber-physical systems have opened up new avenues for healthcare applications [1]. The management of Parkinson's disease (PD) can specifically benefit from these technologies through the provision of continuous monitoring and personalized care for affected individuals [2]. PD is a neurodegenerative condition that causes motor deficits such as tremors, stiffness, and bradykinesia at any stage. The management of these symptoms and the design of a monitoring strategy to determine the progression of disease are important for ensuring appropriate care and timely interventions. However, these activities are not present in the conventional treatment methods, leading to limited insights and delayed responses.

A system combining IoT devices, data collection sensors, and prediction algorithm was proposed to develop a comprehensive framework for continuous monitoring and predictive analysis to address the challenges identified. The integration of wearable sensors, ambient monitoring devices, and smart home technologies into system is to ensure the collection of real-time data on different physiological and environmental parameters. The rich dataset serves as the foundation for developing prediction algorithm to anticipate symptom exacerbation, falls, or medication needs. This is necessary because the requirements to ensure continuous monitoring of symptoms as well as the variations in motor function are one of the obstacles associated with the management of PD. A solution is offered by IoT technology by enabling remote monitoring of patients in real-time to allow medical practitioners to monitor the progress and make informed decisions regarding the appropriate therapy and any necessary alterations to medication.

Embedded systems have been applied in designing several treatment methods throughout the world [3]. These systems were applied in the proposed prototype in addition to machine learning with prediction algorithm. The purpose was to detect brain waves through sensors with the main objective of determining the efficiency of treatment on patients and storing the data in the cloud. Moreover, prediction algorithm was included to habitually monitor the performance of the patients with a focus on the heart rate, blood pressure, temperature, and others. It is important to state that sensors can be placed in different parts of the human body such as the head with the assistance of a cap to detect the brain waves regularly.

IoT-based cyber-physical system was designed for Parkinson's patients in this study through the adoption of prediction algorithm to ensure better quality of life. The process focused on integrating sensors, wearable devices, and machine learning algorithms to collect and analyze data in real-time. The reason was to predict and detect the occurrence of motor symptoms to ensure proactive intervention and personalized care. This study is divided into several parts including Chapter I which explains the introduction, Chapter II discusses the latest study on symptom measurement, Chapter III reviews related works, Chapter IV presents the methods, Chapter V which presents the results and discussion session, and Part VI is the conclusions.

2 The Current State of Symptom Measurement

PD shows significantly different symptoms among individuals diagnosed with the condition. The symptoms range from mild in the earlier stage and are often unnoticed, starting from one side of the body and getting worse on the other [4]. These early symptoms can be measured based on the movement of PD-affected patients with a focus on a particular part or any side of the body. Meanwhile, the analysis of the early signs and symptoms is important to avoid serious complications [5]. For example, the tremor in a limb is often detected through the shivering of hands and fingers, and this can be resolved by rubbing the hands of the affected patients. Stiffness can also occur in any part of the body causing pain in the muscles with limited range of motions limited. Furthermore, disease can make the patients move slower, leading to a high increase in the time consumption rate [6]. It also causes automatic loss of movement which can lead to unconscious movements such as eye blinking, often smiling, and arm swinging during walking as well as change of speech in the form of monotone with the usual inflections [7]. In some other cases, the writing can become scribbled due to the defect known as micro-phobia. Moreover, certain nerve cells such as neurons often break down gradually in PD mainly due to the production of a liquid known as dopamine in the brain [8].

PD is believed to be hereditary in a situation where several members of a family are affected by disease but the occurrence is not common when compared to others such as genetic markers containing a smaller form of risk and exposure to certain toxins [9]. Several studies have also reported that the brain has some Lewy bodies containing clumps of microscopic markers within the brain cells considered to be the main cause of PD. An important example is alpha-synuclein which is a natural and widespread protein. Moreover, some of the risk factors of disease depend on age, heredity, sex, and exposure to toxins. This is confirmed by the results of a previous study that PD is rarely experienced by young adults [10], but sometimes starts in middle age and ordinally in late life. As previously stated, heredity is another factor but the risk is very low except the number of family members affected is low. Furthermore, men are more likely to have disease than women and the people continuously exposed to herbicides and pesticides have a slightly increased risk rate.

Some of the complications of PD include dementia which is associated with difficulty in thinking and is also considered the next stage of disease [11]. However, the cognitive problem is responsive to medications and this is simpler because of the therapy provided for depression which has been initially caused by PD. The emotional changes often found among the affected individuals include fear, anxiety, and loss of motivation. Moreover, the people experience slowed swallowing which leads to drooling and subsequently problems with eating and chewing, choking, and poor nutrition. PD also causes sleeping problems and diseases such as waking up frequently even at night, falling asleep during the day [12], and rapid eye movement during sleep. Some other problems include constipation due to a slower digestive tract, dizziness or lightheadedness when the blood pressure drops suddenly, and difficulty in perceiving differences in certain odors. There is also fatigue and the later stage which causes loss of energy and pains in all parts of the body, specifically the joints. One of the major defects of PD is that sexual desire or performance can be decreased for the affected individuals [13]. Previous study showed that this problem can be moderated through regular aerobic exercises. Another study also stated that caffeine, a substance in coffee, tea, and cola, can also be a risk factor for PD [14].

3 Related Works

A diagnostics tool was developed by [15] for the characterization of a progressive mobility disease to ensure early detection and monitoring of the pathology. This system has the capability of defining modulation of the muscle indexes in real-time through wireless nodes in EMG placed on lower limbs. It was designed using the Altera Cyclone V to convert the data acquired into a binary signal which was subsequently used to determine the muscular indexes and retain information throughout the process. The results of the study were observed to agree with those reported in other clinical literature.

Another study by [16] focused on an easily accessible sensor system designed to monitor the motor symptoms of the cardinal organs. The symptoms identified include rigidity in body parts and the production of tremors in people with PD. At the initial stage, data were directly measured from system but the ability of the sensor system to distinguish between the pre-optimization and post-optimization scenarios was determined in the subsequent stage. The sensor system was developed by integrating three sensing modalities including inertial motion, muscle activity, and force. The specific machine-learning model was able to achieve an average accuracy rate of 90.9% and the feedback was used to assist clinicians in conducting a thorough review. The results from both stages were found to be quite promising and provided an opportunity for additional study.

The study conducted by [17] was used to develop a method to monitor the performance of patients using wearable devices with inertial depth entity. A new wavelet was used to analyze the data collected based on a single wrist-worn smartwatch and was observed to have high detection performance for tremor bradykinesia and dyskinesia. It was also confirmed to be suitable for long-term monitoring of patients at home. Moreover, [18] designed another method by combining data from the inertial sensor worn on the body of patients into multi-dimensional figures to automatically identify dissimilar prescription states. System included signal processing algorithms, time-frequency analysis, and tremor decomposition which were used to calculate the mean frequency, signal power, sparsity, average jerk, and spatial features. The datasets were later tested using a Support Vector Machine (SVM) and the results showed an accuracy of 78%.

The measurement of samples though a non-invasive method to locate the actual position of patients was suggested by [19], [20]. SVM with Principal Component Analysis (PCA) was applied to determine the principal components to be considered in diagnosing PD. The opportunity was used to describe the relationship between SWM and RFE as well as SWM and PLA. Furthermore, the dataset was analyzed through the adoption of incremental, MCS, and hybrid search methods. Another study by [21] also used the voice signals of patients to develop a classification system through the application of algorithms and Random Forests. The statistics, sentences, and pronunciation of particular words were used as the data. The objective determination of the character types in speech signals was proposed to be achieved through an accurate categorization model. Therefore, the highest possible average accuracy obtained for the data acquired was 66.5%.

The motor adjustment in the kinematic constraint related to dissimilar stages of PD was proposed to be categorized in another study. The postural behavior was evaluated using Computerized Dynamic Post-urography equipment based on the analysis of the center of pressure time series to determine Kinematic parameters. The test was in the form of a customized clinical Test of Sensory interface on Balance (mcTSIB), Confines of Stability (LOS), and Cadenced Weight Shift [22]. Furthermore, another system was proposed to differentiate PD from other neurological diseases using Gait characteristics. The feature vectors of the patients were analyzed individually and classified using Gaussian radial basis functions through the SVM. The detection accuracy was calculated to be approximately 83.33% while the feature vectors were determined using the statistical tools. The main drawback was that system could not be used to determine a particular stage of disease but rather to monitor the progress [23].

An effective medical care system developed through IoT was provided for PD patients. The process focused on obtaining the motion metrics virtually by attaching wearable sensors to the clothing of the patients. The sensors were monitored on mobile devices such as tablets and cell phones to virtually retrieve the motion metrics [24]. System was beneficial due to the competence and ability to maximize resources to advance the understanding of the patients. Moreover, the study fully reflected value control, study strategy, and provided an opportunity to understand disease treatment as well as the participation of the patients in the process [25], [26]. Another method was also proposed to adequately distinguish PD patients from normal people using gene expression information [27]. System combined the foundation of a binary-coded genetic algorithm with an extreme learning machine. This hybrid binary-coded generic system was observed to have some complications and problems. However, the application of information about gene expression was able to sufficiently distinguish PD patients from normal people and also determined the subset of genes considered responsible for disease.

A user interface considered suitable for older people with PD was recommended by [28], [29]. System operated on an open-source platform using a mobile device and the interactive interface was designed with a large font, a massive button, an innovative visual line, and considerable feature enrichment appropriate for elderly PD patients. The interface had a high level of accuracy due to the presence of a voice button function, a selectable reply message, and simplicity in the usage through a web browser and a search engine. Another study by [30] primarily focused on monitoring the posture and gait of individuals diagnosed with PD. This was achieved through a wireless body region sensor network consisting of wearable sensors that provided a report of posture and gait kinematic data in real-time and wirelessly. The device was implanted within the human body to ensure it did not interfere with the normal activities of the patients. The purpose was to retrieve data in a natural environment without the patients feeling they were being watched. Moreover, the phenomenon in which the movement performance at home was different from the clinic was later defined as the "white coat performance".

Another method was suggested to diagnose PD by combining stack generalization with a supplementary neural network [31]. System was used to retrieve a speech dataset consisting of different sound recordings from the User Computer Interface (UCI) machine learning repository. This method was further compared with traditional feed-forward backpropagation and complementary neural networks. The results showed that the proposed method had a high level of precision and allowed

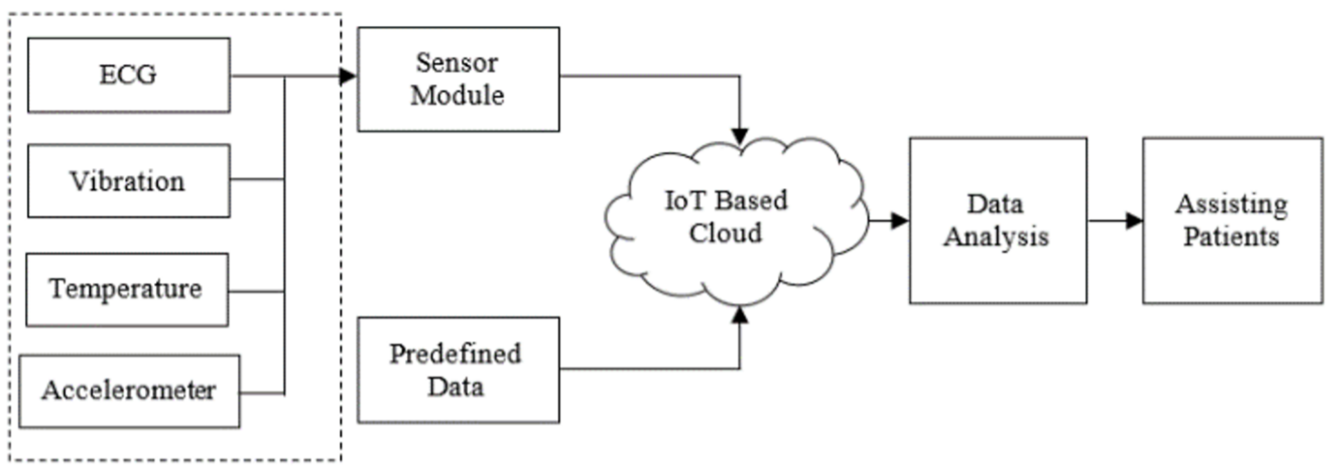

Figure 1: Block diagram of a proposed system.

neural networks to perform more effectively. System was proposed by [32] to save time, ensure more efficiency in determining the posture, and improve the healing process through precautionary recognition classification. This was achieved through the adoption of three types of classifiers as well as significant use of the feature extraction concept. The classifiers categorized the trial samples based on the recognition provided by the training samples, and each classifier relied on its unique categorization.

The wearable gait aid system was expanded to predict the episodes of FOG, ensure patients receive physical assistance when necessary, and determine the feasibility of the device. Moreover, the FOG event prediction method identified a decline in the influence of the gait cycle (GC) on the peak-to-peak value of the toe floor response. The device was capable of detecting a reduction in the gait cycle and subsequently providing the user with a stimulus to prompt knee joint flexion through the control mechanism [33]. Furthermore, an effective method was developed by [34] through the profound belief network and assistance of a significant number of resilient individuals to analyze a PD system. A characteristic blocking process was set up to serve as an impulse to the deep belief network and worn to produce a similar template for the voices to identify specific voices for each individual. The accuracy of this system was recorded to be 94% and higher compared to other methods tested, leading to the determination of its effectiveness in diagnosing PD.

4 Study Methodology

4.1 Microcomputing System

The main dependent of the prototype developed was the microcontroller. Arduino, which was an open-source hardware containing a variety of microprocessors and controllers, was used as the microcontroller in this study. Moreover, interfaces are usually designed between a wide variety of expansion boards and circuits, especially when each board possesses set of digital and analog input/output pins. Boards and interfaces for serial communication were combined with the Universal Serial Bus (USB) to load programs into the computer. Integrated Development Environments (IDEs) were also included based on the processing language projects. The serial Arduino boards applied had a level shifter circuit to alter between RS232 logic levels and transistor-transistor logic (TTL) manner.

4.2 Wearable Sensor Technology

Sensors are quite important in identifying potentially problematic aspects of PD patients. Therefore, several sensors were installed in the proposed prototype including ECG, vibration, temperature, and accelerometer to determine some parameters such as temperature, pressure, heartbeat, vibration, and others. The sensors had higher and lower sensitivities and the appropriate option was selected for the patients. For example, the accelerometer range for normal patients is usually 10-12Hz while PD patients have 40-60Hz. The heartbeat sensors could also detect the changes in the amount of blood in the finger with respect to time and were integrated for pulse sensing applications as shown in the Figure 1.

4.3 Cloud Storage

The cloud storage was mainly used in the proposed prototype to upload the status report of the patients obtained through measurements. The data for normal patients had been previously uploaded while those related to PD patients were uploaded continuously to determine the abnormal conditions. Think Speak, which was IoT platform, was used due to its ability to store different forms of data and accessibility through a computer with internet connectivity to analyze the data and visualize the result. The sensor data were sent to the Think Speak platform from Arduino and other compatible devices, and the results were used to easily identify the mode of the patients.

4.4 Machine Learning with Predictive Algorithm

A machine learning algorithm was used to analyze available data and make predictions. The application of this algorithm is because it is the simplest to avoid issues of local minima, gain a fast mechanism on regression analysis, and offer good generalization performance. The algorithm also has the ability to approximate complex mappings and significantly reduces the time needed for training. The data obtained in the study were uploaded to the cloud allocated with IP address followed by the measurement of quality prediction with accuracy for different iterations using predictive algorithm through statistics of known discrete values. Moreover, the probability of outcome was determined based on a set of input data and only one predictor was used to reduce the complexity. The review of previous studies showed that a significant number of common classifiers in machine learning have been used to diagnose PD. This was considered necessary due to the importance of selecting an appropriate classifier in solving the problems associated with the disease. The complexity of the architecture was reduced in this study by introducing the fuzzy k-nearest neighbor (FKNN) algorithm while keeping the same level of accuracy. The FKNN was developed by Keller et al. based on the premise that fuzzy logic concepts could be used to assign degrees of membership to different classes while considering the distance between an object and its k-nearest neighbors. The points lost to the query point are believed to have a significantly higher contribution to the membership function of respective classes when compared to those that are far away from neighbors. The winning class normally has a higher membership function value compared to the other classes. The uniqueness and competitive advantage of the FKNN is the ability to assign an optimistic value to each projected class.

The KNN is a non-parametric pattern classification method that assigns a class based on the high prevalence among the k-nearest neighbors of the pattern being classified. Meanwhile, the FKNN method is an improved variation of the KNN designed using fuzzy set theory where the fuzzy memberships of samples are not usually assigned to distinct classes as observed in KNN but rather designated to a variety of categories based on the following formula shown in Equation (1) as in

$$U_i(x) = \frac{\sum_{p=1}^{k} U_{ip}\left(\frac{1}{\|X-X_p\|^{\frac{2}{m-1}}}\right)}{\sum_{p=1}^{k}\left(\frac{1}{\|X-X_p\|^{\frac{2}{m-1}}}\right)}, \tag{1}$$

where $p = 1, 2, 3, \ldots, K$ and $i = 1, 2, 3, \ldots, C$ are the number of nearest neighbors and classes respectively. The determination of the membership scale contribution of each neighbor requires using the fuzzy strength parameter m to define how heavily the distance is weighted, and its value is commonly set from one to infinity. Moreover, the Euclidean distance is normally used to calculate the distance metric. U_{ip} is the degree of membership of the pattern X_k from the training set to the class i and can be calculated shown in Equation (2) as in

$$U_{ip}\left(X_k\right) = \begin{cases} 0.51 + 0.49\left(\frac{n_p}{K}\right), \\ 0.49\left(\frac{n_p}{K}\right), \end{cases} \tag{2}$$

where n_p is the numbers of neighbors which belong to the p^{th} class.

The calculation of all memberships for the query sample was followed by the allocation to the class with the highest membership value. The results from several studies show that feature extraction is an extremely important part of the classifier modeling process, particularly for medical applications. The purpose is to turn an input parameter vector into a feature vector and lower the dimensionality of the feature vector. These tasks are normally accomplished by lowering the dimensionality of the input parameter vector. Moreover, PCA is a well-known feature extraction tool that searches for the most important changes in the initial feature space with the main objective of improving the classification process, in terms of accuracy and efficiency. This study focused on determining the effectiveness of using PCA for feature extraction in PD diagnosis problems.

The FKNN model was later applied for classification using the feature set newly constructed by PCA and the initial stage of the process was to configure all the parameters. The fuzzy strength was identified to have a sizeable influence on the performance of the FKNN algorithm and this led to the adoption of an experimental method to determine the ideal value for the parameter. The main concept was to supply the fuzzy membership value m with a range of $[1, 2]$ and a step size of 0.01 followed by a test on the classification performance using a 10-fold cross-validation on numerous numbers of neighbors k. Moreover, the average accuracy reached by FKNN for each of the possible values of m was determined through cross-validation analysis. The value with the highest level of accuracy on average was selected as optimal for the fuzzy strength parameter. This process was followed by the application of the FKNN classifier to the feature set reduction to compute the classification accuracy and an average of the results were later calculated.

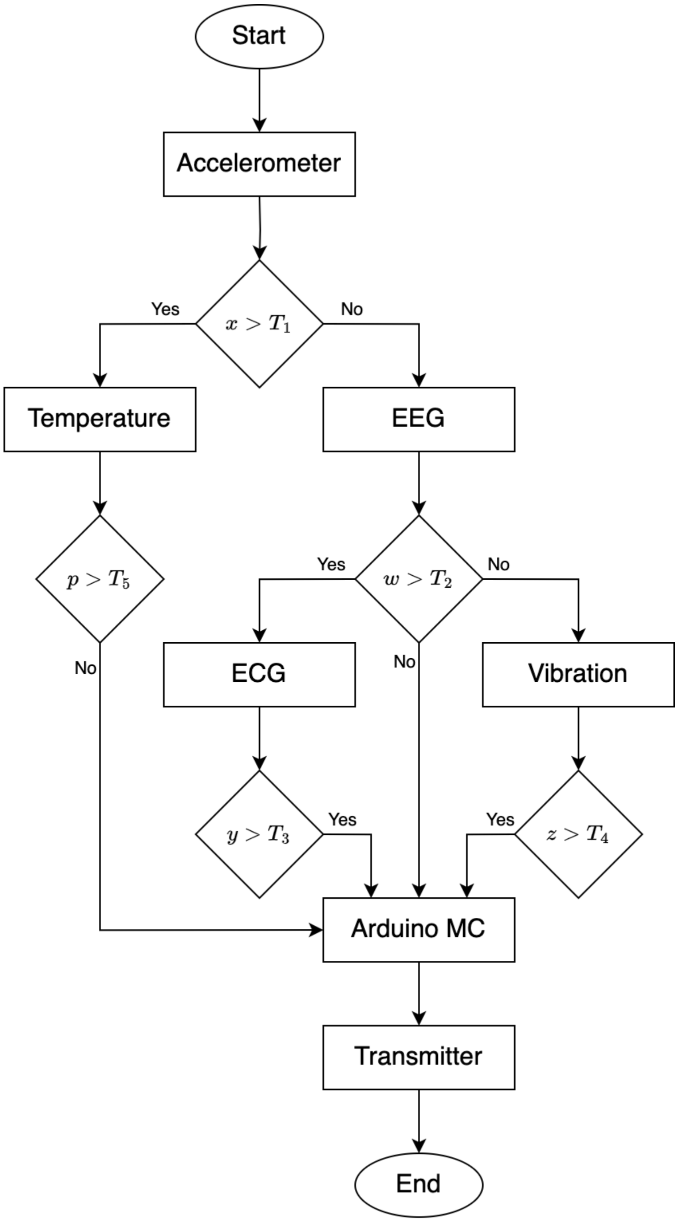

Figure 2: Flowchart of normal condition.

4.5 Methodology

The operations of the proposed prototype mainly depended on the sensor data uploaded to the cloud storage to provide a new treatment option for PD patients. Prediction algorithm was used to regularly track the progress of the patients and automatically save the information to the cloud. The data from the cloud were used to consistently analyze the performance of the patients. Moreover, the sensors could be placed in the body of the patients through different means such as the head through the assistance of a cap to detect the brain waves regularly. System did not have the capacity to provide complete relief to the patients but it could assist in reaching the lifetime.

4.6 Data Analysis

4.6.1 Normal Condition

The condition of PD patients was mainly determined through the comparison with normal persons. This was achieved through the processes described in the flow presented in the Figure 2.

The Pseudo code for the Normal Condition is described as follows:

- Start the program
- IF x>T1, then ENTER Temperature AND EEG

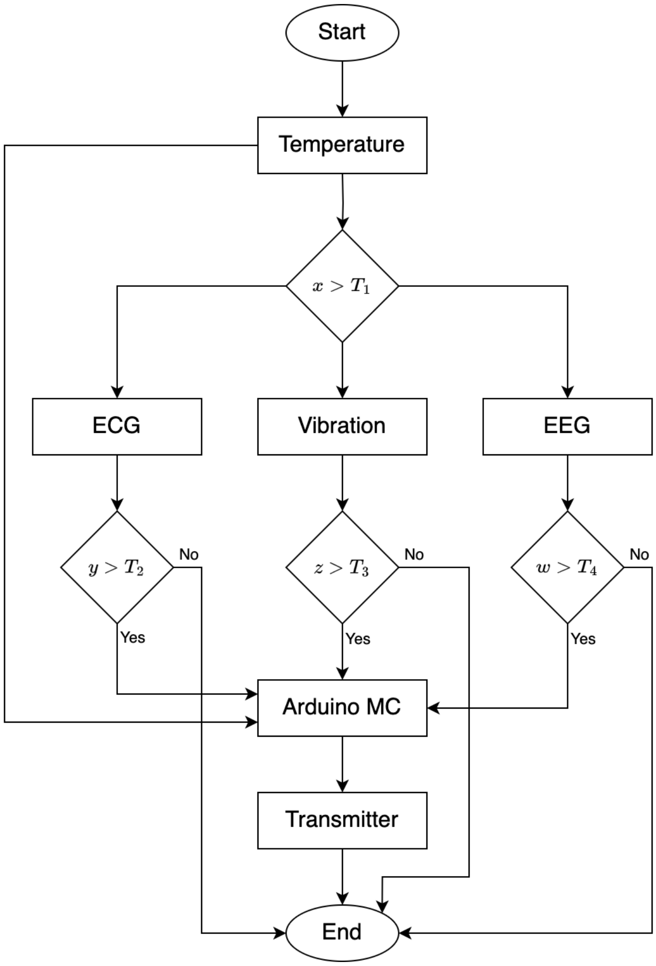

Figure 3: Flowchart of abnormal condition.

- IF Temperature p<T5, then ENTER Arduino MC
- IF EEG w>T2, then ENTER ECG and Vibration
- IF ECG y>T3, then ENTER Arduino MC
  ELSE STOP
- IF Vibration z>T4, then ENTER Arduino MC
  ELSE STOP
- Stop the program

4.6.2 Abnormal Condition

The functional flow of the abnormal condition was easily diagnosed through the proposed prototype. The rate of risk zone for the patients was defined to alert the caretaker. This was achieved by measuring the temperature first followed by the other parameters such as heartbeat and vibration. PD was characterized by an abnormally high degree of synchronization of the quantitative EEG signal rate in the frequency range of 13–30 Hz and other conditions stated in Figure 3.

The Pseudo code for the Abnormal Condition is described as follows:

- Start the program
- IF x>T1, then CHECK ECG, VIBRATION, and EEG
- IF ECG y>T2, then ENTER Arduino MC
  ELSE STOP
- IF EEG w>T4, then ENTER Arduino MC
  ELSE STOP
- IF Vibration z>T4, then ENTER Arduino MC ELSE STOP
  item Stop the program

Table 1: Performance comparison.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Positive Predictivity (%)
Fuzzy k-nearest neighbor	94.14	96.03	90.91	94.77
SVM	91.63	93.33	88.76	93.33
Decision Tree	87.45	89.54	83.72	90.73
Naïve Bayes	88.07	92.11	81.32	89.17

5 Results and Discussions

The values from the vibration, temperature, EEG, ECG, and accelerometer sensors were analyzed to decide whether the condition of the patients was abnormal or normal. The proposed prototype captured brain metabolism and Prediction Algorithm was used to foresee the incentive associated with a specific range of the data obtained. Moreover, the diagnostics and analysis of different conditions were expected to increase the awareness of the physical therapist about the discomfort level of the patients. The proposed prototype ensured a ray of hope tempered with realism and was developed through the use of a MATLAB simulation environment and an Intel i7 CPU with NVIDIA GPU 1650 ti. Data were obtained from participants consisting of senior citizens in different age categories with an average age of 64.52 years old and the overall sample size was 239.

The normalization process was conducted to prevent numerical difficulties during the computation and to ensure the characteristics extracted in higher range ranges did not overpower those in lower ranges. Moreover, 10-fold cross-validation was used to objectively measure the classification generalization. The most important advantage of this method was that each of the test sets was autonomous, thereby increasing the dependability of the outcomes. One of the ten subsets was selected at random to serve as the test set for each iteration while the remaining nine were used as the training set. The process was followed by the computation of the standard deviation of the total error for all ten sets. The data were partitioned according to the participants selected with the assurance of having the same sample proportion in each of the data subsets as the population. The purpose was to guarantee that the classification performance in each subset was the same. Furthermore, the conduct of 10-fold cross-validation just once could not produce sufficient classification accuracies for comparison. It is also not possible to predict the accuracy of a model e at any given iteration with absolute certainty because the division of datasets was inherently random. Therefore, 10-fold cross-validation was conducted ten times to obtain an accurate evaluation of the functionality of the datasets, and the average of the results was determined.

The effectiveness of the proposed prototype was evaluated through the application of the FKNN classifier to the original feature space and the results were compared with the Naive Base, Decision Tree, and SVM classifiers. The performance of the proposed prototype was evaluated based on classification accuracy, sensitivity, specificity, and positive predictivity, which are represented as shown in Equation (3), (4), (5), and (6) as follow

$$\text{Accuracy } (\%) = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \times 100, \tag{3}$$

$$\text{Sensitivity } (\%) = \left(\frac{TP}{TP + FN}\right) \times 100, \tag{4}$$

$$\text{Specificity}(\%) = \left(\frac{TN}{TN + FP}\right) \times 100, \text{ and} \tag{5}$$

$$\text{Positive predictivity}(\%) = \left(\frac{TP}{TP + FP}\right) \times 100. \tag{6}$$

The results obtained from comparing the classifiers are presented in the following Table 1. The FKNN method had a 94.14% accuracy rate while the Decision Tree, SVM, and Naive base algorithms had 87.45%, 91.63%, and 88.07%, respectively. Moreover, the FKNN had the highest sensitivity and specificity values with 96.03% and 90.91%, respectively. The FKNN also recorded the greatest positive predictivity rate of 94.77%, while the SVM, DT, and NB had 93.33%, 90.73%, and 89.17%, respectively.

The results showed that FKNN had the best level of accuracy with 94.14% while the Naive Base had the worst. The FKNN also had the least False Negative (FN) and False Positive (FP) conditions compared to the other methods while the Naive Base had the most as presented in the following Figure 4.

The sensitivity comparison in Figure 5 showed that the FKNN had the highest value of 96.03% while the Decision Tree had the lowest with 89.54%. This was associated with the existence of the fewest FN or highest TP in the FKNN compared to the other methods while the Decision Tree had the opposite. This sensitivity comparison graph can be seen in Figure 5. Moreover, specificity usually measures the ability of a model to correctly identify negative instances or true negatives. It also quantifies the proportion of actual negative instances correctly classified. The parameter can be used to compare the number of TN and FP and is considered useful in scenarios where negative instances need to be correctly identified such as medical diagnostics. The results showed that the FKNN had the highest specificity of 90.91% and this was an indication the method had the most TN and less FP values compared to the others. Meanwhile, the Naive Base had the lowest value of 81.32% which showed the method contained the lowest TN and most FP values as presented in Figure 6.

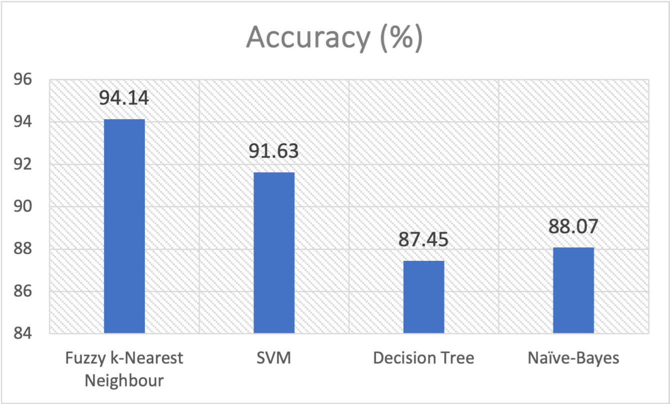

Figure 4: Accuracy comparison.

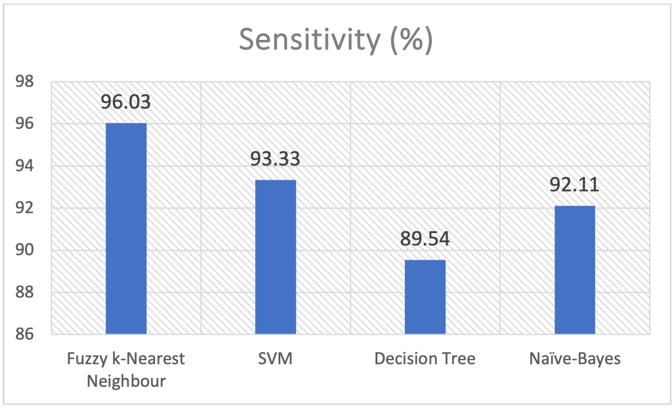

Figure 5: Sensitivity comparison.

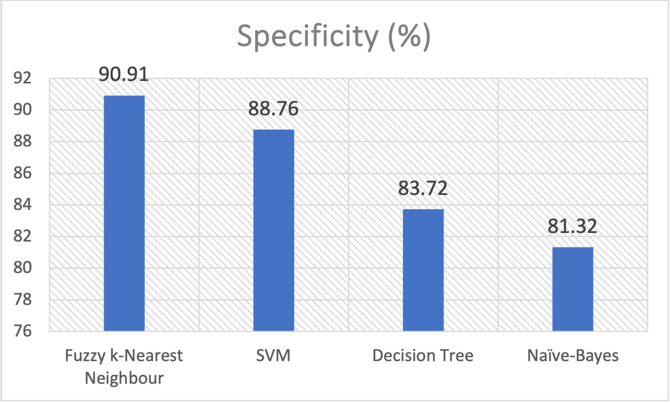

Figure 6: Specificity comparison.

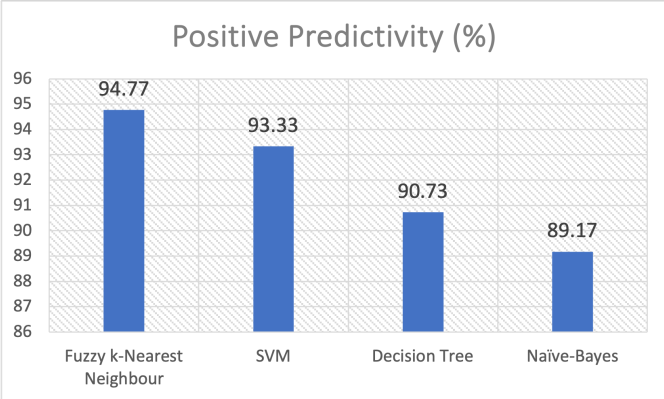

Figure 7: Positive predictive comparison.

Positive predictive value (PPV) is a performance metric used in classification tasks to measure the accuracy of the positive predictions made by a model. It is defined as the ratio of true positive predictions to the total number of positive predictions. The phenomenon shows that PPV quantifies the proportion of positive predictions considered to be correct. The results showed that the FKNN had the highest value of 94.77% as indicated by the most TP and least FP values recorded compared to the other methods. Meanwhile, the Naive Base had the worst value of 89.17% which showed the existence of the least TP and most FP values. The result of positive predictive value can be seen in Figure 7

6 Conclusions

In conclusion, the prototype was proposed to make PD patients live easier daily lives without any sort of disturbances. This was achieved using individuals with severe cases of PD as the primary participants and the results showed that the prototype was reliable, cost-effective, and correctly monitored the ability of the sensors used to perform several functions. The prototype was expected to reduce the mortality rate and liberate users from both day and night clinical assistance. Moreover, the FKNN-based prediction algorithm developed was found to be more accurate than other algorithms as showed by the 94.14% accuracy recorded.

Authors' Contributions

In this study, all authors studied and designed the article.

Competing Interests

The authors declare that they have no conflict of interest.

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