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*RESEARCH ARTICLE / ARAŞTIRMA MAKALESI*

# Machine Learning-Based Real-Time Tremor Level Detection for Parkinson Disease

## Parkinson Hastalığı için Makine Öğrenimi Tabanlı Gerçek Zamanlı Tremor Seviyesi Saptanması

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### Abstract

Parkinson's disease is one of the neurodegenerative diseases that affects neurons in the brain and causes motor functions to deteriorate. The most common symptom of this disease is involuntary tremor, especially in the hands and fingers, when the patient is in a resting position. In this study, a machine learning-based embedded system is proposed that can detect tremor and determine its level according to sensor data obtained from fingers. Subsequently, tremor data was obtained using Arduino UNO and MPU-6050 sensor, machine learning models were trained, and autonomous decision making have been performed. The study aims to evaluate tremor autonomously in real time, report it to the specialist, and assist in diagnosis and treatment. Unlike the studies in the literature, in this study, tremor signals were processed in real time with machine learning techniques instead of rule-based decision making. Tremor signals are digitally generated using sensors via the Internet of Things. Since mobility is crucial in the healthcare industry, the data was transferred wirelessly to the local server and evaluated for ease of use. As a result of this study, 96% accuracy was achieved using artificial neural networks in tremor level detection. By increasing the amount of data and the number of participants, the potential for the system to be developed and used in clinics is quite high.

***Keywords:*** *Machine Learning, Internet of Things, Parkinson Disease, Real-Time Diagnostics, Tremor Detection*

### Öz

Parkinson hastalığı beyindeki nöronları etkileyerek motor fonksiyonlarının bozulmasına neden olan nörodejeneratif hastalıklardan biridir. Bu hastalığın bilinen en yaygın belirtisi hastanın dinlenir pozisyondayken özellikle el ve parmaklardaki istemsiz tremordur. Bu çalışmada el parmaklarından elde edilen sensör verilerine göre tremoru tespit ederek, seviyesini saptayabilen makine öğrenmesi tabanlı bir gömülü sistem önerilmektedir. Arduino UNO ve MPU-6050 sensörü kullanılarak tremor verileri elde edildikten sonra makine öğrenmesi modelleri eğitilerek otonom karar verme işlemi yapılmıştır. Çalışmanın amacı tremoru gerçek zamanlı, otonom olarak değerlendirebilmek, uzmana raporlama yapmak, teşhis ve tedavi işlemine yardımcı olmaktır. Literatürde bulunan çalışmalardan farklı olarak bu çalışmada kural tabanlı karar vermek yerine tremor sinyalleri gerçek zamanlı olarak makine öğrenmesi teknikleri ile işlenmiştir. Tremor sinyalleri nesnelerin interneti aracılığıyla sensör kullanılarak sayısal olarak üretilmiştir. Sağlık sektöründe mobiliteye önem verildiği için kullanım kolaylığı sağlaması amacıyla veriler kablosuz olarak yerel sunucuya aktarılarak değerlendirme yapılmıştır. Çalışma sonucunda yapılan deneyler ile tremor seviye tespitinde yapay sinir ağları kullanılarak %96 başarı elde edilmiştir. Veri miktarı ve katılımcı sayısının arttırılmasıyla birlikte sistemin geliştirilme ve kliniklerde kullanılma potansiyeli oldukça yüksektir.

***Anahtar Kelimeler:*** *Makine Öğrenmesi, Nesnelerin İnterneti, Parkinson Hastalığı, Gerçek Zamanlı Teşhis, Tremor Tespiti*

## 1. Introduction

Parkinson's disease is a neurodegenerative disease that can occur with age-related risks of both environmental and genetic factors [1]. Although some risk factors have been identified, the cause of this disease in many patients is not fully known, except for genetic factors. It causes dopamine deficiency due to neuron losses in the brain region called substantia nigra, causing impairment of motor functions, affecting mobility and involuntary tremors [2]. Tremor is clinically defined as involuntary, rhythmic, and variable movements of one or more limbs of the body [3]. In Parkinson's disease, tremor is seen in different parts of the body at different frequencies. Involuntary tremor movements, especially those that occur while at rest, are common in Parkinson's disease [4]. Despite this, movement tremor is also observed in patients [5]. The use of devices with sensitive measurement capabilities in the diagnosis of the disease allows the specialist to determine the tremor frequency. Using Internet of Things (IoT) devices as an alternative to the existing devices is very suitable for solving this problem.

IoT devices have been widely preferred in wearable technologies in recent years [6-11]. Reducing the size of sensors and microcontroller cards and designing them to consume less energy allows their use with wearable technologies. Through smart watches and wearable smart textiles, the sensors people carry can collect health-related data such as the number of steps and heart rate [12-13]. In this way, interpreting the collected data and turning it into meaningful results has an important place in the field of health, as in many other fields. In addition, the data obtained can be transferred to a central server or mobile device using wireless technologies and stored and processed there. After the stored data is pre-processed, various predictions are made using artificial intelligence technologies [14-16]. The

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predictions made are reported and forwarded to experts in a way that supports the diagnosis process, making it easier to evaluate people's health status.

There are many studies in the literature on the use of IoT devices in the field of healthcare. Using IoT devices, basic health parameters such as people's pulse values, body temperature, electrocardiography (ECG) signals, and oxygen saturation are collected and transmitted wirelessly to mobile devices via Bluetooth [17-20]. Data obtained with IoT technologies used in the field of healthcare can be analyzed with machine learning and deep learning techniques [21-23]. A secure health information model has been proposed for the confidentiality of patient information in health information systems, including IoT technologies [24]. In the field of healthcare, IoT-based decision support systems are used to facilitate the diagnosis and treatment process [25]. With the use of IoT-based wireless body area networks and radio frequency identification (RFID) technology integrated into this system, a system that includes collecting physiological data of the patient with sensors that can be worn on the patient, remote monitoring of the patient and, data analysis has been presented [26].

In the study conducted by Raza et al., an IoT-based system that allows remote monitoring of patients in a closed environment was proposed [27]. They stated that the proposed system detects the progression of Parkinson's disease using auditory inputs with machine learning techniques. AlZubi et al. have proposed an IoT-based wearable device [28]. In the proposed system, IoT sensors are placed in the patient's brain to collect brain features. The collected data is continuously analyzed to predict changes in the brain. Zhao et al. proposed a wearable anklet that can measure and grade the gait characteristics of Parkinson's patients [29]. In their proposed system, they detected and classified the abnormal gait patterns of patients using the K-nearest neighbor algorithm. Saleh et al. proposed a system based on artificial intelligence of things that can detect Parkinson's patients through voice disorders [30]. They used four different machine learning algorithms in their proposed system. In the study conducted by Belyaev et al., they proposed a system that allows the diagnosis and monitoring of Parkinson's disease in an IoT environment using resting EEG signals [31]. They used a machine learning algorithm in their proposed system.

In this study, after tremor data was obtained through IoT devices, it was processed, and level detection estimation was made with machine learning methods. In addition, it is aimed to transfer the data to the server in real-time and wirelessly and to obtain results by evaluating them in a short time. The proposed prototype helps the diagnosis process by estimating the numerical measurement and severity of tremor, which cannot be perceived by humans in a short time. However, it is thought to play an important role in treatment planning.

The next section contains the materials and methods, the hardware used in the study, the data collected through the hardware, data processing and machine learning models used in tremor prediction are explained. The third section contains the experiments and their results. The last chapter contains the results of the study and the discussion section.

## 2. Materials and Methods

The proposed system consists of two parts: hardware and software. The first part includes embedded system hardware that contains sensors to detect tremor in the fingers. In the second part, there is software developed for the application of tremor level detection estimation and machine learning models. After collecting the data, the designed hardware transmits it to the server in real-time and wirelessly. Then, with the software developed, the data are interpreted in this unit and presented to expert opinion. In this section, hardware details, how the data is obtained and processed, and finally the application of tremor level detection estimation and the machine learning models used will be discussed.

### 2.1. Circuit design

The following hardware components are used in the proposed circuit design.

• Arduino UNO microcontroller board,

• MPU-6050 sensor,

• HC-05 Bluetooth module.

Arduino UNO microcontroller was used to process the data received from the sensor and make it ready to be sent to a mobile device, computer, or a server. Arduino UNO can be powered from the USB port, power socket input or Vin input. In the created design, power was provided via the USB port. Arduino UNO is a microcontroller that is quite suitable in terms of capacity for processing sensor data and is low-cost compared to other embedded systems. To detect tremor, an MPU-6050 sensor card with a 3-axis angular accelerometer and 3-axis gyroscope was used. MPU-6050 converts analog signals to digital with its 16-bit analog-to-digital converter. MPU-6050 sensor board communicates with Arduino UNO via I2C protocol. SDA and SCL pins of the MPU-6050 sensor are connected to the A4 and A5 analog input pins on the Arduino UNO for I2C communication. 5 Volt and Gnd pins on Arduino were used for voltage supply of the MPU-6050 sensor. Additionally, the Int pin on the MPU-6050 is connected to the Digital 2 pin on the Arduino. HC-05 Bluetooth module was used to transfer the data processed with Arduino UNO to the mobile device or server. Wireless serial communication was achieved by connecting the HC-05 module to the TX and RX pins of the Arduino UNO microcontroller card. 3.3 Volt and ground pins of the Arduino UNO board were used for the voltage supply of the HC-05 module. The HC-05 module is paired with the server where the data is collected via Bluetooth connection. The serial communication information flow rate (baud-rate) of the HC-05 module is defined as 38400. The circuit diagram of the proposed hardware design is shown in Figure 1.

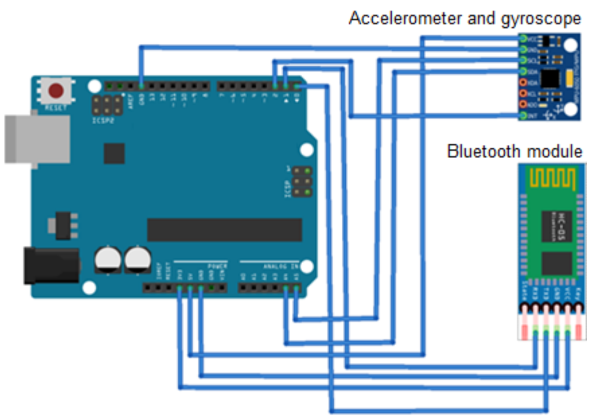


**Figure 1.** Circuit diagram of the proposed design.

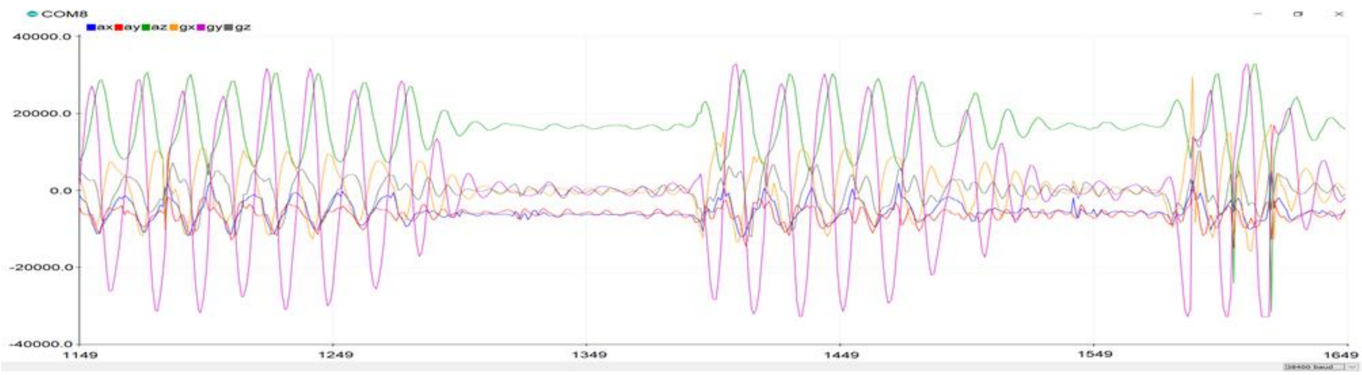


**Figure 2.** The gyroscope and acceleration data.

### 2.2. Collection of data

With the designed system, a mechanism was created to collect tremor data. Gyroscope and accelerometer data of x, y and z axes were obtained with the values transferred from the MPU-6050 sensor to the Arduino UNO board. Gyroscope and accelerometer data are vectors that each contain three axes information. The device is connected to the server wirelessly using the COM8 port. Afterwards, the six-axis data produced in real-time were colored and visualized as in Figure 2.

Each color represents different axis information regarding gyroscope and acceleration. After all the data were visualized and examined, the vector data containing the axis information was transferred wirelessly to the server via the Bluetooth module. The operating frequency of the MPU-6050 sensor is determined as 100 Hz. In the created mechanism, the MPU-6050 sensor was positioned on the participants' fingers. Data collection was conducted with three different participants, whose identities and demographic information were kept confidential to ensure blind data conditions. Each participant was tested for approximately fifteen seconds, during which uninterrupted real-time data was recorded and transmitted to the server. Tremor measurements were taken and recorded while the participants were in a resting and sitting position. The data was generated at varying intensities within the experimental environment, allowing the models to be trained and evaluated for estimating different tremor levels.

**Processing of data**

Data obtained from sensors are often subject to varying amounts of noise or the presence of outliers, which can interfere with accurate analysis. This issue is particularly pronounced when working with high-sensitivity sensors, as their increased precision often comes at the cost of heightened susceptibility to noise. While high-sensitivity sensors are advantageous for capturing detailed and subtle variations in signal data, the presence of unwanted noise can complicate the data analysis process, potentially leading to incorrect interpretations and erroneous decisions. Numerous noise removal techniques have been proposed in the literature [32-34] to address these challenges. These methods aim to enhance the quality of the signal data by minimizing noise and outliers, thereby improving the reliability and accuracy of subsequent analyses.

In the present study, a high-sensitivity sensor was employed to collect time series data. Consequently, the need to eliminate noise from the raw data emerged as an essential step in the preprocessing pipeline. A moving average filter (MAF), a widely used noise removal technique in signal processing, was applied to achieve this. It operates by smoothing the signal data, reducing the effects of random noise while preserving the essential trends and patterns within the signal.

The calculation of the MAF is mathematically expressed in Equation (1). In this equation, the $i^{th}$ filter output is denoted by MAF[i], the $i+j^{th}$ filter input is denoted by x[i], the frame value or number of points is denoted by WS.

During the computation process, the filter assigns the arithmetic mean of the preceding data points, determined by the specified frame size, to the current filter output ($i^{th}$). By calculating the average over a defined window of data points, this method effectively reduces the impact of noise and outliers in the signal, producing a smoother and cleaner representation of the original data. In this study, a real-time filter with a frame value of three (WS=3) was applied to each of the time series signals obtained from the sensors. The application of this filter successfully smoothed the signals, ensuring that unwanted noise and discrete irregularities were eliminated.

To illustrate the effectiveness of the study, the process was applied to the z-axis gyroscope data generated by the sensor. The results are presented in Figure 3, where the red signal represents the unfiltered z-axis data, clearly demonstrating the presence of significant noise. After applying the filter, the processed signal is displayed in blue, showing a much smoother profile. It is evident from the figure that the blue signal is constrained within a smaller range compared to the noisy red signal, indicating that the noise has been effectively removed. This preprocessing step significantly enhances the quality of the time series data, making it more suitable for downstream machine learning tasks.

In addition to noise reduction, further preprocessing steps were applied to the time series data to prepare it for multivariate machine learning models. Since the collected data consists of variables with varying numerical value ranges, these differences could potentially introduce biases during the training of machine learning algorithms. To address this, the minimum-maximum normalization method was employed to scale all variables to a common range between zero and one. This normalization technique ensures that features with larger numerical ranges do not disproportionately influence the learning process of the model, thereby improving the performance and stability of the machine learning algorithms. By standardizing the numerical ranges of the variables, the time series data was effectively transformed into a format that is both uniform and compatible with the requirements of the applied machine learning models.

$$MAF[i] = \frac{1}{WS}\sum_{j=0}^{WS-1} x[i+j] \tag{1}$$

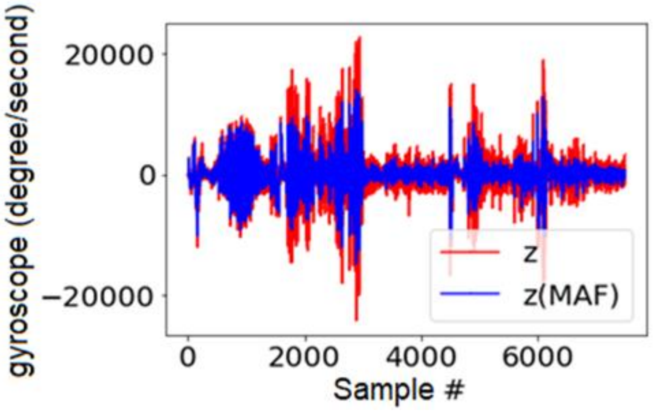


**Figure 3.** Filtering gyroscope data on the Z-axis.

The preprocessing steps of noise removal and normalization through the minimum-maximum method played a critical role in ensuring the quality and usability of the sensor data. These steps not only improved the clarity of the signals by removing unwanted noise but also standardized the data for optimal performance in multivariate machine learning applications. Together, these methods provide a robust framework for preparing high-sensitivity sensor data for predictive modeling and analysis.

### 2.3. Time series forecasting model

In this study, machine learning models were employed to predict tremor levels from multivariate time series data, which represent complex temporal patterns of tremor dynamics. By conducting experiments with a variety of models, the most effective approach for achieving accurate predictions was identified. Considering that the system is intended to operate in real-time environments, an artificial neural network (ANN) architecture with a minimal number of parameters and layers was selected to optimize computational efficiency while maintaining high prediction accuracy.

As depicted in Figure 4, the selected ANN model consists of two hidden layers, each designed to capture the underlying relationships in the input data efficiently. Specifically, the first hidden layer comprises 64 neurons, while the second hidden layer contains 32 neurons. These layers are in addition to the input and output layers, which facilitate the mapping of the input features to the predicted tremor levels. To ensure computational efficiency and robust training, the Rectified Linear Unit (ReLU) activation function was utilized in the hidden layers. This choice of activation function not only accelerates the convergence of the model but also helps to mitigate the vanishing gradient problem that can occur during backpropagation. The error calculation for model training was performed using the mean squared error, which is a standard metric for evaluating the deviation between predicted and actual values in regression-based tasks.

The training process of the ANN model was further optimized using the Adam optimizer, a state-of-the-art optimization algorithm known for its adaptability and efficiency in handling sparse gradients. Adam combines the advantages of both momentum-based and adaptive learning rate optimization techniques, making it well-suited for complex and high-dimensional datasets like the multivariate time series data used in this study. Since the task involves multi-class classification predicting discrete tremor levels the output layer employs a softmax activation function, which converts the raw model outputs into probability distributions across the classes. The predicted class is determined by selecting the class with the highest probability.

For comparative analysis, two additional models were developed using Support Vector Machines (SVMs). These models were designed with different kernel functions to evaluate their performance on the tremor prediction task. The first SVM employed a linear kernel, which assumes that the data can be separated using a hyperplane in the input feature space. In contrast, the second SVM used a non-linear kernel, specifically the radial basis function (RBF) kernel, which can capture more complex relationships by mapping the input data to a higher-dimensional space. The use of the RBF kernel enables the non-linear SVM to effectively handle data that are not linearly separable, providing a more flexible model for the classification task.

The comparison between these models highlights the strengths and weaknesses of each approach in terms of accuracy, computational efficiency, and real-time applicability. The ANN model, with its lightweight architecture and efficient training process, demonstrated superior performance for real-time applications, making it the preferred choice for this study. The inclusion of SVM models, however, provides a valuable benchmark and demonstrates the potential of alternative machine learning methods in tremor prediction.

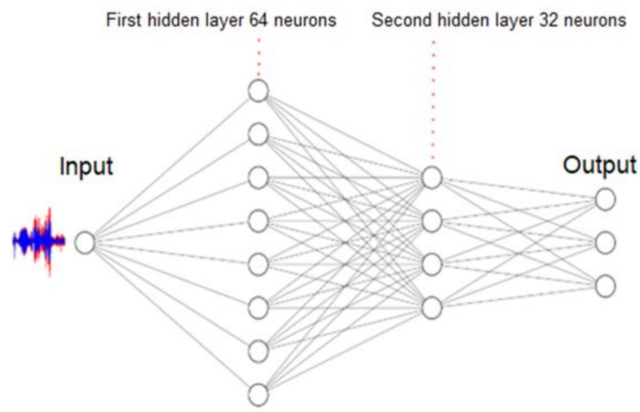


**Figure 4.** Applied artificial neural network model.

## 3. Experiments and Results

In the experiments, multivariate time series data containing gyroscope and acceleration information obtained after pre-processing were created and level estimation was made with artificial neural networks and support vector machines. Data on all axes (x, y, z) generated from the gyroscope and acceleration sensors were evaluated. To determine the tremor level, training and testing were performed with time series data recorded at different intensities. In each session, tremor data obtained from the participants over a certain period of time were evaluated. Tremor data obtained in the resting position in the experimental environment were evaluated with different models and compared. A total of 225 tremor data of equal numbers belonging to three levels: normal, mild tremor and severe tremor were used. Instead of testing on a randomly selected data set, k-fold cross validation was applied with a k value of five.

In the ANN model, 800 epochs of training were performed for each layer. Comparison of linear (L) and non-linear (NL) support vector machines (SVM) and ANN models according to accuracy metric is given in Table 1.

**Table 1.** Performance comparison of the models.

| | Model | | |
|---|---|---|---|
| | **SVM (L)** | **SVM (NL)** | **ANN** |
| 1st Layer | 93.3 | 97.78 | 97.78 |
| 2nd Layer | 95.56 | 95.56 | 97.78 |
| 3rd Layer | 82.22 | 91.11 | 95.56 |
| 4th Layer | 80.0 | 95.56 | 95.56 |
| 5th Layer | 82.22 | 88.89 | 93.33 |
| Avg. Accuracy | 86.67 | 93.78 | 96.0 |

Linear SVM with radial basis function showed approximately 7% lower performance in terms of accuracy than non-linear SVM. Additionally, the created ANN model performed better than both SVM models.

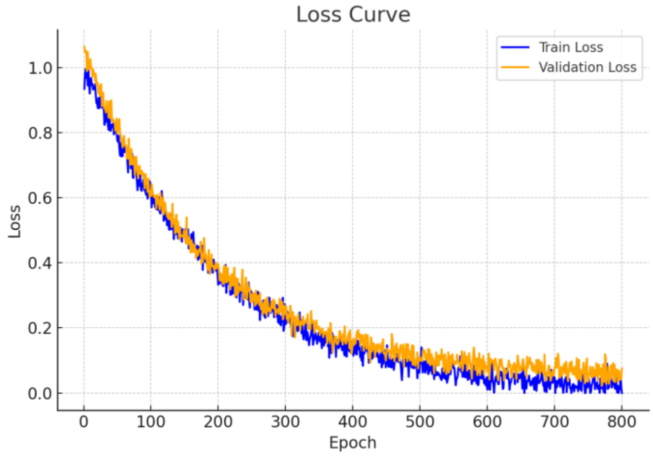


**Figure 5.** Training and validation loss curve of the ANN model.

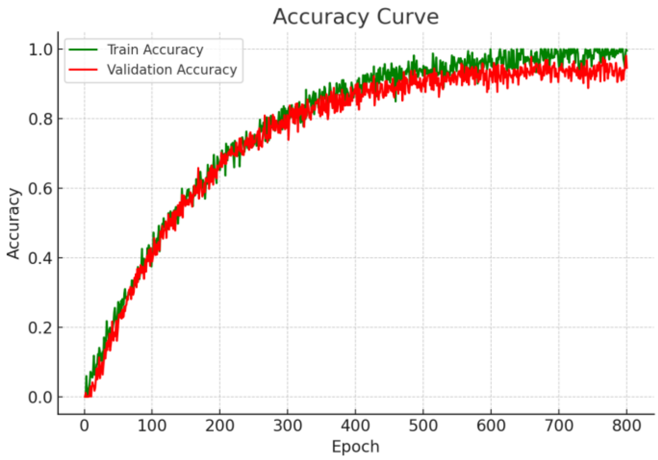


**Figure 6.** Training and validation accuracy curve of the ANN model.

The training and validation loss curves are presented in Figure 5 and Figure 6 that exhibit a consistent downward trend over the course of 800 epochs, indicating effective convergence of the ANN model. The relatively small gap between training and validation losses throughout the training process suggests a well-generalized model with minimal overfitting. This observation is consistent with the high average validation accuracy of 96% obtained across the five folds.

Fluctuations observed in the validation loss are attributed to the inherent difficulty in distinguishing between adjacent tremor classes, particularly the mild tremor class. This is corroborated by the confusion matrix results, which indicate that most classification errors occurred in differentiating mild tremor from the normal and severe tremor classes. The asymptotic behavior near 1.0 indicates that the model achieved a high level of classification performance over time. The stability of both loss and accuracy curves across epochs supports the robustness of the training process under the five-fold cross-validation protocol. This further reinforces the reliability of the ANN model in the context of multivariate time series classification involving gyroscope and accelerometer signals for tremor level estimation.

The confusion matrix of the 5th layer of the ANN model with the worst accuracy value is given in Figure 7. While there is no error in the tremor class, it is seen that one sample from the normal class and two samples from the mild tremor class were classified incorrectly. In all the experiments, it was observed that machine learning models made mistakes mostly in detecting mild tremor.

**Table 2.** Performance metrics by classes.

| | Metric | | |
|---|---|---|---|
| | **Precision** | **Recall** | **F1** |
| Tremor | 0.80 | 1.00 | 0.89 |
| Mild Tremor | 1.00 | 0.88 | 0.94 |
| Normal | 1.00 | 0.94 | 0.97 |
| Macro Average | 0.93 | 0.94 | 0.93 |

Table 2 shows the performance of the classification model across the three groups: Tremor, Mild Tremor, and Normal. It breaks down Precision, Recall, and F1-score for each class, giving us a clearer picture of how well the model distinguishes between them. For the Tremor class, the model achieved a Precision of 0.80. This means that when the model predicted Tremor, it was correct 80% of the time. Even more impressively, the Recall was perfect at 1.00, the model identified every actual Tremor case without missing any. This strong combination leads to an F1-score of 0.89, which nicely balances these two metrics. The Mild Tremor category showed the highest Precision at 1.00, indicating that all predicted Mild Tremor cases were indeed correct. However, the Recall was a bit lower at 0.88, suggesting the model missed some Mild Tremor cases and labeled them as something else. The F1-score of 0.94 still reflects very strong overall performance here. For the Normal group, the model performed excellently as well, with both Precision and Recall above 0.94. This resulted in an F1-score of 0.97, showing the model's ability to classify normal subjects nearly perfectly. These results suggest that the model is reliable across all three categories. It's particularly good at precisely identifying Mild Tremor and Normal subjects, and it's highly sensitive in detecting Tremor cases. This balance between metrics makes it well-suited for real-world use where correctly distinguishing between these motor conditions is crucial.

The proposed system has the advantage of real-time decision-making, unlike most of the studies carried out for level determination. In a study similar to this study, prediction was made using linear regression to determine the tremor level [35]. The value obtained as a result of the regression is expressed as a numerical value between one and seven. In this study, classes representing certain levels were used instead of expressing the output with a numerical value. In addition, since this study is a real-time IoT system, it is aimed to work with high performance in all experiments.

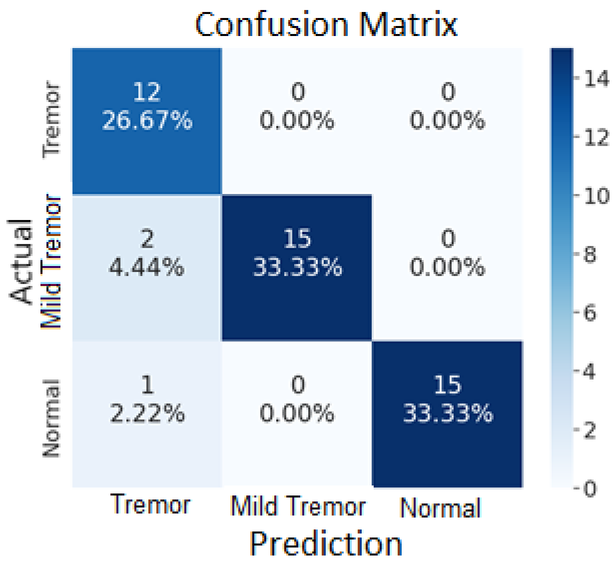


**Figure 7.** Confusion Matrix of the ANN for Tremor Levels.

Unlike the related study, the data was expressed and evaluated as a multivariate time series after pre-processing, without going through the feature extraction process. In another study [36], employed a mobile phone accelerometer to measure the acceleration of tremors in Parkinson's disease patients. In contrast, our implementation has its own designed IoT device specifically designed for tremor measurement. They achieved 95% accuracy. Building on recent advances, similar real-time monitoring approaches have been demonstrated by [37], who developed a wrist-worn wearable system leveraging deep learning for continuous tremor detection in naturalistic settings. In another study [38], they proposed a magnetic sensor-based system for real-time tremor tracking aimed at enabling immediate clinical feedback. These studies highlight the critical role of real-time, wearable technologies in Parkinson's disease management. Our proposed system aligns with and advances this trend by offering a highly customizable, clinical-grade IoT solution capable of accurate and immediate tremor classification, thus enhancing the potential for practical application in healthcare and patient monitoring.

## 4. Result and discussion

In this study, tremor data was collected using IoT devices specifically designed to measure and monitor hand tremors in patients with Parkinson's disease. These devices enabled the wireless transmission of data to a central server, where the data was processed in real time using advanced computational methods. A prototype system was developed to predict tremor severity levels by employing machine learning algorithms. The proposed system aims to provide specialists with analyzed and interpretable data to assist in the diagnosis and treatment processes.

In order to create the dataset for this study, multivariate time series data was generated by simulating various tremor levels with differing intensity values. Tremor data was recorded under controlled conditions, specifically in resting and sitting positions, to ensure consistency and accuracy in the measurements. Using these data, multiple machine learning models were developed and evaluated for their performance in detecting tremor severity levels. Among the models evaluated, artificial neural networks (ANNs) achieved the highest accuracy rate of 96%, making them the most effective approach for this task.

The results of this study highlight the potential of IoT-based systems in healthcare applications, particularly for monitoring and managing neurodegenerative diseases such as Parkinson's disease. The integration of machine learning methods with IoT technology provides a powerful tool for analyzing tremor patterns and predicting severity levels in real time. By offering specialists a detailed interpretation of tremor data, this system has the potential to serve as a valuable aid in clinical decision-making, improving both diagnosis and treatment outcomes.

Looking ahead, the study proposes the development of deep learning models as a natural progression to the machine learning-supported signal processing model currently in use. Deep learning approaches are expected to provide more robust and reliable predictions due to their ability to automatically extract complex features from raw data. By identifying patterns and nuances in tremor signals, these models could significantly enhance the understanding of tremor dynamics in Parkinson's patients, providing the medical community with more comprehensive insights.

Future research directions include expanding the dataset by increasing the number of participants and obtaining the necessary ethical permissions to test the system in clinical settings. A larger and more diverse dataset will enable more extensive validation of the system, leading to improved performance and reliability in real-world scenarios. With an increase in data volume, the predictive capabilities of the system are expected to improve, paving the way for its integration into clinical practice. Ultimately, the goal is to establish a reliable, scalable, and clinically validated tool that can be widely used to support the medical community in diagnosing and managing Parkinson's disease.

## Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval, as all data was anonymized and no identifiable personal or demographic information was collected, ensuring blind data conditions.

This article has no conflicts of interest with any individual or institution.

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