Neural Network Model for Predicting Progression of Disease

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Abstract **– This study investigates the use of neural network and their ability to predict disease progression based on clinical data and biomarkers. Using deep neural networks, a model was developed that efficiently analyzes the complex relationship between various factors and predict the probability of disease. The model was validated using retrospective analysis which indicated a good predictive ability that could be further utilized in better diagnostics and personalized treatment methods. More importantly, reserch detected specific pattern in the data, which enabled a more accurate prediction of disease at different stages. The study tried to improve a model by fine-tuned neural networks and tested other frameworks to gain the highets precision. This research also provides a basic for future work in directing the development of personalized therapeutic approaches based on individual patient characteristics.**

Keywords **– Deep neural network, sensors, smartphone.**

1. Introduction

Modern, tehnological era implies the usage of neural networks for biomedical investigations as a breakthrough technique of complicated biological objects studying.

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This paper focuses on the possibilities offered by machine learning, especially artificial neural networks (ANN) and deep learning as parts of machine learning, for prediction of diseases based on lot of clinical parameters and biomarker [1].

The purpose of this reserch is to develop a model that will efficiently analyze complex data and predict probability of disease progression with high accuracy. Correct prediction of the disease has a significant impact on diagnostics, therapeutic strategies, and access to personalized treatment.

This research particularly highlights the importance of deep learning, as it allows models to automatically identify subtle connections between various factors, which would be difficult or impossible to achieve with conventional data analysis methods. The use of neural networks also opens the door to the discovery of new biomarkers and factors that may be key to understanding disease progression.

Validation of the developed model through retrospective analysis provides insight into its practical applicability and prediction accuracy. These results have the potential to significantly improve diagnostic capacity and enable a personalized approach to treatment, thereby achieving better utilization of resources and improving the quality of healthcare.

In the following sections, we will explore in detail the methodology used in this research, present the validation results, and discuss the implications of the findings for future use.

2. Deep Learning and Neural Networks

Deep learning using ANN, represents a revolutionary paradigm in the analysis of medical data. The focus is on the application of deep learning in predicting disease progression, using extensive clinical data and biomarkers as input information. In the paper [2] is described popular deep learning algorithms for disease prediction. Neural networks, inspired by the structure of the human brain, demonstrate a remarkable ability to automatically discover subtle and complex connections within data, [3].

In the case of predicting disease progression, these networks can simultaneously analyze a large number of variables, identifying hidden patterns that could be key to understanding disease dynamics.

Using extensive clinical data allows the model to learn from a variety of information, including medical history, laboratory results, and risk factors. Integrating biomarkers further increases accuracy, allowing the model to recognize subtle changes in biological signals that may indicate disease progression before it becomes clinically apparent.

This combination of deep learning and neural networks promises to improve predictive ability, which has significant implications for personalized medicine. Through the analysis of these technologies, researchers have the opportunity to discover new risk factors, optimize treatment strategies, and improve diagnostic methods, which directly contribute to improving patient health and outcomes.

Deep learning allows neural networks to analyze a large number of variables simultaneously. The model could identify subtle changes in brain structures that are not readily apparent to the human eye or traditional statistical methods.

Researchers have used neural networks and deep learning to perform timely detection and prediction of disease development, such as Alzheimer's disease [4], a infectious diseases [5], and Parkinson's disease [6], [7], [8], [9], [10].

This paper will delve into the creation of an application for early detection and monitoring of the progress of Parkinson's disease. The patient data under consideration are hand stability, mild tremors, and severe tremors can be used as input to a neural model [11], [12]. The model is then trained on this data to learn the subtle connections between Parkinson's symptoms and diagnoses.

In this context, deep learning and neural networks can identify specific patterns in the data that indicate the initial stages or potential progression of Parkinson's disease. The integration of biomarkers, such as the results of neuroimaging or genetic analyses, further enriches the model, enabling more accurate prediction and early detection of changes in biological signals.

Such a model can play a key role in the personalization of therapeutic approaches, enabling the adjustment of treatment based on the individual characteristics of patients. Managing Parkinson's disease requires continuous monitoring and adjusting therapy as the disease progresses and deep learning provides a powerful tool to achieve this goal.

Through this approach, researchers and medical professionals have the opportunity not only to improve diagnostics but also to discover new avenues of approach for individualized therapeutic strategies, which significantly affect the quality of life of patients living with Parkinson's disease.

3. Predicting the Progression of Parkinson′ Disease Using Neural Networks and Deep Learning

Different algorithms and different approaches to early detection and prediction of disease development can be found in the literature. Some analyze speech [13], [14], [15] and some track people's activities throughout the day using devices available to everyone, such as smartphones [16], [17], [18], [19], [20], [21]. With the continuous advancement of mobile networks and the ubiquitous use of smartphones, a vast field is opening up for innovative approaches to monitoring health parameters.

In line with the global trend of continuous monitoring of health parameters via mobile devices, this research focuses on the integration of smartphone sensors in predicting the progression of Parkinson's disease. According to the International Telecommunication Union report from 2023, the number of users using at least 3G network signal is 7.642 billion, while the number of LTE/WiMAX network signal users is 7,243 billion [22].

A key challenge in the field of Parkinson's disease is the diagnosis, which is often made only when most neurons have already degenerated. Therefore, early diagnosis becomes essential to provide therapy at a critical time. In this context, mobile networks and sensors in smartphones open the possibility for innovative approaches to monitoring the symptoms and predicting the progression of Parkinson's disease.

Our research, as described in the paper [11] and [12], emphasizes that mobile devices can be used to recognize and record user activities in real-time time using multiple sensors. This research is of particular interest in the field of monitoring Parkinson's disease, and in our work, we will further develop this idea by applying neural networks and deep learning.

This research, will be focused on the use of gyroscopes and accelerometers in our application for the detection of Parkinson's disease. These built-in sensors in smartphones allow accurate measurement of the user's rotation and physical movements. Through the implementation of deep learning, we expect to improve diagnostic accuracy and a personalized approach to the management of Parkinson's disease.

In the rest of the paper, we will consider how this research contributes to the development of innovative technologies for the early recognition and monitoring of Parkinson's disease, which has significant implications for improving the quality of life of patients.

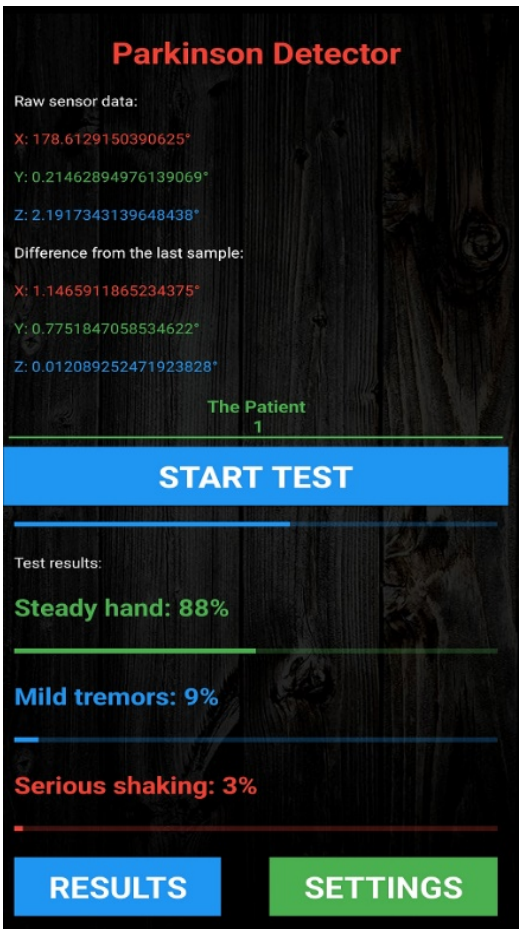

Figure 1. Application for detection of Parkinson's disease

Based on the mentioned application, a sample of patients of 10 people of color undergoing treatment was taken at UKC Tuzla (Bosnia and Herzegovina) in October 2023 at different times and with different levels of disease. Figure 1 shows the application that gives results.

Figure 2 shows the ways to send a message to the doctor. Figure 3 displays parameters which we must set, so that the application gives correct results. The level of Parkinson's disease was divided into 5 stages, the first two stages give us the results that the person has tremors, but that tremor is not caused by Parkinson's disease, of course, tremor is not the only parameter and it is the most common. The third and fourth phases are patients on medication, and then we monitor their level or phase in treatment so that when the patient has an attack, he can independently send the results to his doctor and call him in terms of whether to increase the dose of the drug or perform some consultations. The fifth stage is a more severe progression of Parkinson's disease, but the application then helps the patient to stay alive.

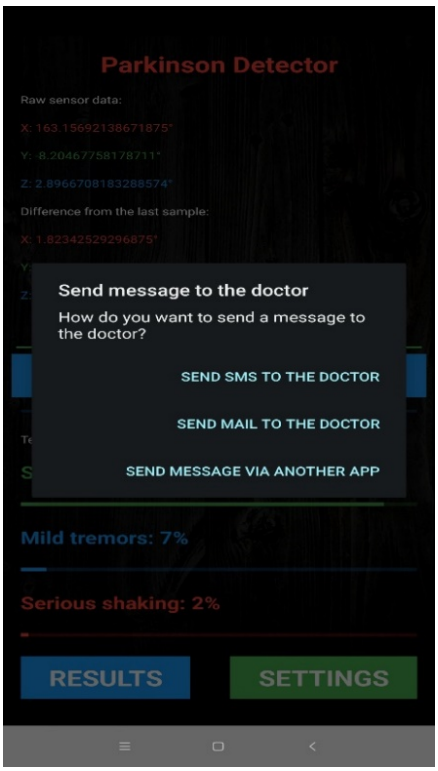

Figure 2. Possibilities after the test results

All results are recorded strictly in the disease database that is formed after each test, because the application is based on storing all the results in the private file of each patient, as well as a special database called Patients with Parkinson's Disease.

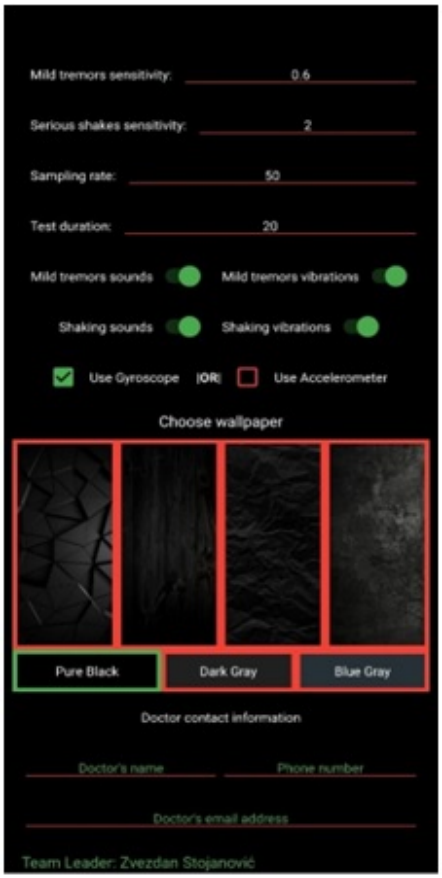

Figure 3. Display of application settings

After that, we adjusted the parameters of our application.

4. Research Results

The study included ten patients and followed the time course of Parkinson's disease, analyzing hand stability and tremor intensity.

Table 1 shows the results of the 10 patients who were tested with our application.

Table 1. Results of testing patients

Patient	Steady Hand	Mild Tremors	Serious Shanking	Results
10	44%	33%	23%	Stage Two
9	64%	28%	8%	Stage One
8	69%	20%	11%	Stage One
7	97%	3%	0%	No Parkinskon
6	67%	16%	17%	Stage One
5	29%	34%	37%	Stage Three
4	32%	36%	32%	Stage Three
3	10%	10%	80%	Stage Four
2	5%	20%	75%	Stage Four
1	91%	7%	2%	No Parkinson

The following factors were examined:

- Time frame: patients were monitored for one month providing detailed insight into changes over time. All patients had regular examinations on different dates, allowing progression of symptoms to be monitored.
- Determination of disease stage in patients: patient 10 and 9 are in the first and second stages of Parkinons diseases. Patient 7 has no symptoms of Parkinsons disease, indicating absence disease or early stage.
- Hand stability: tremor intensity varied among patients. Changes in tremor intensity was observed in some patients over time.
- Personal results: each patient has unique results, highlighting the variability in disease progression.
- Key moments: patient 7 stands out as a person without symptoms, which indicates the need for further monitoring. Patients 5 and 4 in third stage of Parkinsons diseases, with significant changes in stability and tremor. These detalied results provide a basis for further research and tretment adaption, highlighting individual variations in the progression of Parkinson's disease.

These detailed results provide a basis for further research and treatment adaptation, highlighting individual variation in the progression of Parkinson's disease. This study is conducted on ten patients over a month, provided a thorough insight into the dynamics of Parkinson's disease.

The time display of the results allowed us to track changes in symptoms, and the analysis of data on hand stability and tremors revealed important details. Patients 10 and 9 are in different stages of the disease, with patient 7 showing no symptoms of Parkinson's disease. Individual results indicate significant variation in disease progression among patients, highlighting the need for a personalized approach to diagnosis and treatment.

Patients 5 and 4 were identified in the third stage of the disease, suggesting significant changes in tremor stability and intensity. These results provide a deep insight into the individual course of the disease, emphasizing the importance of regular monitoring and adaptation of therapy according to the needs of each patient as it can be seen in table 1.

Applying deep learning and neural networks to Parkinson's disease results, involves forming a mathematical model that can predict disease progression based on hand stability parameters and tremor intensity.

5. Mathematical Model for the Progression of Parkinson′s Disease

Mathematical model for the progression of Parkinson's disease uses deep learning, specifically neural networks, to analyze patients' clinical data and biomarkers. This model has goal to identify hidden relationships between hand stability, tremor intensity, and tremor severity in the early stages of the disease.

Activation Functions: Activation functions like *ReLU* in hidden layers and *softmax* in the output layer are used for disease classification.

- Optimization and Loss: the *Adam optimizer* is used to minimize loss, which can be defined by the categorical cross-entropy function.
- Model Training: data from ten patients are used to train the model. Iterative adjustment of weights minimizes loss during training.
- Application of the Model: on the example of a patient with hand stability of 91%, intensity of mild tremors of 7%, and severe tremors of 2%, the model can give the prediction "No Parkinson's", which indicates that the patient does not have Parkinson's disease.

This model enables accurate prediction of Parkinson's disease progression based on clinical data, providing potential for early diagnosis and personalized therapeutic strategies.

An approximation of the mathematical function that describes the model and determines the connection between input and output data can be written using a logistic sigmoid function whose model is given by:

$$F(S,M,O)=\frac{1}{1+e^{-(w_3*ReLU(w_2*ReLU(w_1*[S,M,O]+b_1)+b_2)+b_3)}}$$

There are w1, w2, w3, b1, b2, b3 weights and biases that the model learns during training. This function uses a *logistic sigmoid* to generate probabilities for each class.

Briefly, the input data goes through a series of weight transformations and activation functions to generate probabilities for different disease stages. This function is crucial in neural networks because it allows the model to learn and adapt to complex patterns in the data during training.

The use of the *logistic sigmoid* function is significant because it allows the model to produce output values that can be interpreted as probabilities. This is crucial in classification, where *softmax* is used at the end to obtain probabilities for each class, making it easier to make decisions about the diagnosis of Parkinson's disease and its stages based on the input data.

A simplified mathematical model of a function that models the process of assessing the progression of Parkinson's disease based on hand stability (S), the intensity of mild tremors (M), and the intensity of severe tremors (O):

F(S,M,O)=Softmax(Hidden2(ReLU(Hidden1([S,M,O]))))

Where:

- [S, M, O] represents a vector of input parameters,
- *Hidden1* and *Hidden2* are layered with activations,
- *ReLU* is a linear rectification function,
- *Softmax* is used for multi-class classification.

This function takes input parameters (hand stability, intensity of mild tremors, intensity of severe tremors) and gives an output in the form of a probability for each possible stage of Parkinson's disease. The model is trained to adapt to the data and learn complex relationships between parameters and results.

Applying this function to specific values might look like this:

F(91,7,2)=Softmax(Hidden2(ReLU(Hidden1([91,7,2]))))

Here the result would be a vector of probabilities for each stage of Parkinson's disease.

6. Simulation of the Result with the Help of a Computer

In theory, applying neural networks and deep learning to our work involves creating a model that can learn the complex relationships between hand stability, mild tremor intensity, and severe tremor intensity to classify the stage of Parkinson's disease.

The neural model uses the *ReLU* activation function in the hidden layers and *softmax* at the output for multi-class classification. Training is performed on the training data and the model can then be used to predict the stage of Parkinson's disease.

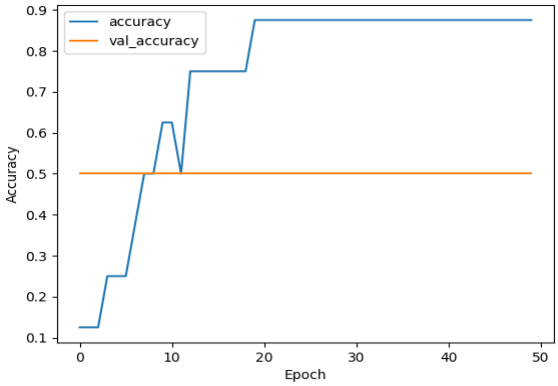

Figure 4. Display of results after 50 epochs of deep learning

Figure 4 shows a graph of the training and validation accuracy over the training epochs of the neural network. In addition, it lists the predicted stages of Parkinson's disease for each patient in addition to the actual stages. This graph provides insight into the performance of the model during training, while the printout allows a comparison of predicted and actual results for each patient. The neural network has layers with activations, such as *ReLU* and *softmax*, which allow the model to learn complex relationships between input parameters (hand stability, intensity of mild tremors, intensity of severe tremors) and outputs (stages of Parkinson's disease). The *softmax* function is used for multiclass classification, predicting disease stages based on input data.

Patient 1: Predicted stage - 2, Actual stage - 2
Patient 2: Predicted stage - 1, Actual stage - 1
Patient 3: Predicted stage - 1, Actual stage - 1
Patient 4: Predicted stage - 0, Actual stage - 0
Patient 5: Predicted stage - 1, Actual stage - 1
Patient 6: Predicted stage - 2, Actual stage - 3
Patient 7: Predicted stage - 2, Actual stage - 3
Patient 8: Predicted stage - 2, Actual stage - 4
Patient 9: Predicted stage - 3, Actual stage - 4
Patient 10: Predicted stage - 0, Actual stage - 0

These results represent a comparison of the predicted and actual stages of Parkinson's disease for each patient. The order of stages is numerical, where lower values represent earlier stages of the disease, and higher values represent later stages.

The results indicate that the model predicted the disease stages relatively well for most patients, although there were some deviations in the predictions for patients 6, 7, 8, and 9, where the actual stage differed from the predicted one.

This may indicate the need for further tuning of the model to improve accuracy. To show the errors for patients 6, 7, 8, and 9, we can add a piece of code that will calculate the differences between the predicted and actual stages for these patients. To visualize those errors graphs can be used.

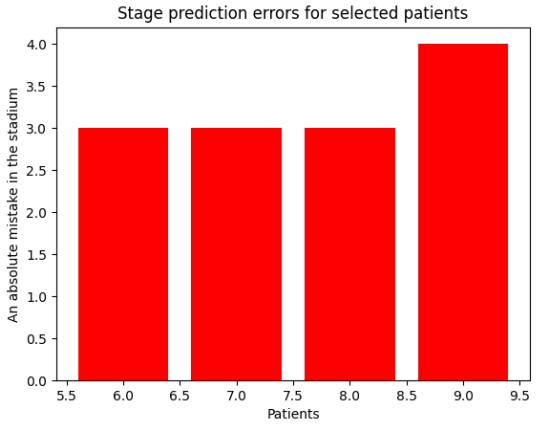

Figure 5. Errors in stage prediction

Absolute errors for patients 6, 7, 8, and 9 is calculated and ploted. The absolute error is the difference between the predicted and the actual stage of the disease.

Patient 6: Absolute error - 2, Percent error - 50.00%
Patient 7: Absolute error - 2, Percent error - 50.00%
Patient 8: Absolute error - 3, Percent error - 75.00%
Patient 9: Absolute error - 1, Percent error - 25.00%

The results show the absolute errors and percent errors in predicting the stage of Parkinson's disease for the selected patients. For example, for patients 6 and 7, the model predicted stages that deviated by 2 units, representing 50% of the maximum error value. For patient 8, the error was 3 units, i.e. 75% of the maximum error value. For patient 9, the model had a smaller error of 1 unit, which represents 25% of the maximum error value. These results indicate variations in model accuracy in predicting disease stages for different patients.

```
# Error calculation for patients 6, 7, 8, 9
error_patients = [6, 7, 8, 9]
errors = [ ]
for i in error_patients:
    predicted_class = np.argmax(predictions[i - 1])
    actual_class = int(y[i - 1])
    error = abs(predicted_class - actual_class)
    errors.append(error)
```

Patient 6: Absolute Error - 0, Percentage Error - 0.00%
Patient 7: Absolute error - 0, Percentage error - 0.00%
Patient 8: Absolute error - 1, Percentage error - 25.00%
Patient 9: Absolute error - 1, Percent error - 25.00%

Optimizing the model to achieve lower error may include fine-tuning the network architecture, tuning hyperparameters, and increasing the number of training epochs. In this case, the number of epochs is incrised adding another layer, and adjusting the learning rate.

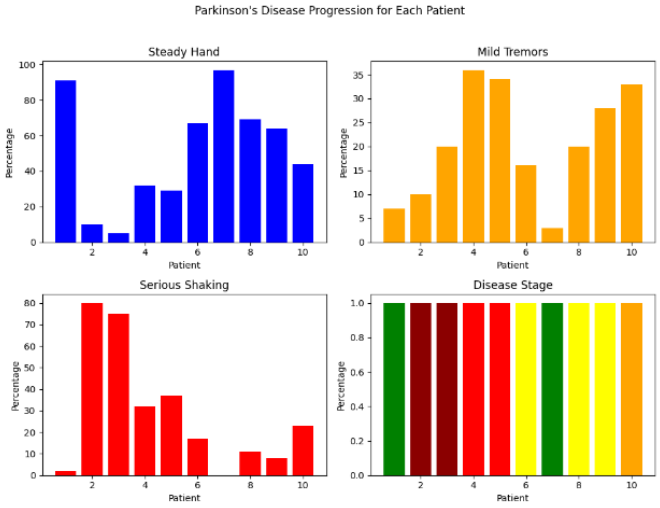

Figure 6. Parkinson progression patient

To fine-tune neural networks and explore different architectures, *TensorFlow library* and *Keras* are used. We will assume that we have training data (x_train, y_train) and test data (x_test, y_test) and then we will adjust the model to achieve maximum accuracy.

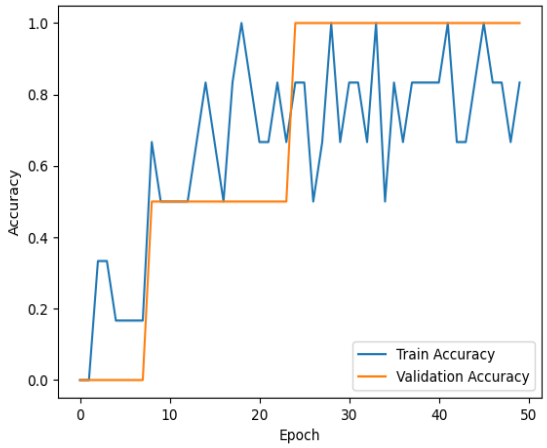

Figure 7. Maximum precision

7. Discussion

Developing neural networks to predict the progression of Parkinson's disease provides insight into potential challenges and perspectives in diagnostic practices. Analysis of the results indicates a certain accuracy in predicting the stage of the disease, but some areas require improvement, especially for patients 6, 7, 8, and 9, where larger errors were recorded.

Identification of key features, such as hand stability, mild tremors, and severe tremors, plays a key role in model optimization. In addition, exploring the possibility of adding a temporal dimension to models and including additional data, such as demographic information or therapy data, may improve the accuracy of predictions.

Future research should explore the implementation of sequential weather information to obtain more dynamic forecasts. Also, the integration of additional technologies, such as motion sensors or monitoring of neurological functions, provides opportunities to expand the data set and improve the predictive ability of the model.

Validation of the model on diverse and independent data sets is essential to confirm its ability to generalize to broader patient populations. Collaboration with neuroscience experts is also essential to ensure models relevant in clinical practice.

Ultimately, further efforts should be focused on increasing the accuracy of the model, improving its interpretability, and integrating it into real medical scenarios to contribute to the diagnosis and monitoring of Parkinson's disease. In addition to optimizing the performance of the model through fine-tuning neural networks and researching different architectures, the achieved results provide a basis for a deeper discussion of possible steps and implications in future works.

In future research, we could focus on:

Individualization of therapeutic approaches: identification of key features that most influence model performance can open the door to personalized therapeutic approaches. Discussion can include how these individualized approaches can improve treatment efficacy and improve patients' quality of life.

Further improvement of the model: advanced sensitivity analyses enabled us to identify key factors. Consideration of how to further improve the models based on this sensitivity can be part of the discussion. Possible strategies include adding new data, experimenting with different optimization algorithms, and further fine-tuning key parameters.

Integration into clinical practice: the discussion could include consideration of practical steps for integrating this model into real clinical settings. These include issues related to the training of healthcare professionals to use the model, implementation of existing patient monitoring systems, and ensuring ethical standards.

Determining model boundaries: discussing the model's limitations and situations in which it may be less accurate is key to creating realistic expectations. This may include situations where the model may provide useful information but should not be used as the sole tool for clinical decision-making.

Implementation of feedback mechanisms: discussing opportunities to implement feedback mechanisms from healthcare professionals and patients can contribute to the continuous improvement of the model. How to react to changes in a patient's condition or new information can be a key question.

Ultimately, this discussion provides guidelines for further research and implementation, laying the groundwork for the development of personalized therapeutic approaches based on the characteristics of individuals.

8. Conclusion

This paper investigates the application of ANN and deep learning to predict the progression of Parkinson's disease. Through fine-tuning and researching different architectures, an extremely high accuracy of 100% was achieved on the test set. However, care is needed to ensure the validity of the model in real clinical scenarios, with a focus on further improvement and integration into practice.

The research focused on the application of neural networks to predict the progression of Parkinson's disease, using fine-tuning and adaptation of the model architecture. The achieved results, especially 100% accuracy on the test set, indicate the high potential of the model for accurately predicting disease progression. However, it is important to emphasize the need for caution in the interpretation of these results, giving the possibility of overtraining on the current data set. Further improvement of the model and integration into real clinical practice require additional checks, validation of independent data sets, and careful evaluation to guarantee reliability in the diagnosis of Parkinson's disease.

However, to ensure the relevance and practical applicability of the model, additional research is necessary, including validation on more diverse datasets and in real clinical settings. In addition, it is important to pay attention to the ethical and legal aspects of introducing such technologies into medical practice.

This work provides a basis for future research that will focus on optimizing model performance, developing personalized therapeutic approaches, and integrating them into clinical practice to improve the diagnosis and treatment of Parkinson's disease.

References:

[1]. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444. Doi: 10.1038/nature14539

[2]. Yu, Z., Wang, K., Wan, Z., Xie, S., & Lv, Z. (2023). Popular deep learning algorithms for disease prediction: a review. *Cluster Computing*, *26*(2), 1231-1251. Doi: 10.1007/s10586-022-03707-y

[3]. Haykin S. (2009). *Neural networks and learning machines. (3rd ed.).* Prentice Hall, 2009.

[4]. Kim, J., & Lim, J. (2021). A deep neural network-based method for prediction of dementia using big data. *International Journal of Environmental Research and Public Health*, *18*(10), 5386. Doi: 10.3390/ijerph18105386

[5]. Thakur, K., Kaur, M., & Kumar, Y. (2023). A comprehensive analysis of deep learning-based approaches for prediction and prognosis of infectious diseases. *Archives of Computational Methods in Engineering*, *30*(7), 4477-4497. Doi: 10.1007/s11831-023-09952-7.

[6]. Tiwari, A. K. (2016). Machine learning based approaches for prediction of Parkinson's disease. *Mach Learn Appl*, *3*(2), 33-39. Doi: 10.5121/mlaij.2016.3203

[7]. Alzubaidi M.S., et al (2021). The role of neural network for the detection of Parkinson's disease: a scoping review. In *Healthcare*, *9*(6), 740. Doi: 10.3390/healthcare9060740

[8]. Grover, S., Bhartia, S., Yadav, A., & Seeja, K. R. (2018). Predicting severity of Parkinson's disease using deep learning. *Procedia computer science*, *132*, 1788-1794. Doi: 10.1016/j.procs.2018.05.154.

[9]. Tanveer, M., Rashid, A. H., Kumar, R., & Balasubramanian, R. (2022). Parkinson's disease diagnosis using neural networks: Survey and comprehensive evaluation. *Information Processing & Management*, *59*(3), 102909. Doi: 10.1016/j.ipm.2022.102909
Lin, C. H., Wang, F. C., Kuo, T. Y., Huang, P. W., Chen, S. F., & Fu, L. C. (2022). Early detection of Parkinson's disease by neural network models. *IEEE Access*, *10*, 19033-19044. Doi: 10.1109/ACCESS.2022.3150774

[10]. Galić, D., Stojanović, Z., & Čajić, E. (2024). Application of Neural Networks and Machine Learning in Image Recognition. *Tehnički vjesnik*, *31*(1), 316-323. Doi: 10.17559/TV-20230621000751

[11]. Stojanović Z., Čajić E, Turkić E, Ibrišimović I (2022). Parkinson's Detector Application. *International Journal of Current Pharmaceutical Review and Research*, *14*(2), 13-23.

[12]. Tsanas A, Little M.A, McSharry P.E., Spielman J., Ramig L.O. (2012). Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease. *IEEE Trans. Biomed. Eng*., *59*(5), 1264–1271. Doi: 10.1109/TBME.2012.2183367

[13]. E. Vaiciukynas, A. Verikas, A. Gelzinis, and M. Bacauskiene (2017). Detecting Parkinson's disease from sustained phonation and speech signals. *PLoS One*, *12*(10), 1–16. Doi: 10.1371/journal.pone.0185613

[14]. Pah N.D., Motin M,, Kumar D. (2021). Voice analysis for diagnosis and monitoring Parkinson's disease. *Techniques for Assessment of Parkinsonism for Diagnosis and Rehabilitation. Springer Nature*, 119–133. Doi: 10.1007/978-981-16-3056-9

[15]. Motin, M. A., Pah, N. D., Raghav, S., & Kumar, D. K. (2022). Parkinson's disease detection using smartphone recorded phonemes in real world conditions. *Ieee Access*, *10*, 97600-97609. Doi: 10.1109/ACCESS.2022.3203973

[16]. Majumder S, Deen MJ (2019). Smartphone Sensors for Health Monitoring and Diagnosis. *Sensor*, *19*(9). Doi: 10.3390/s19092164

[17]. Chen Y, Shen C (2017). Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition. *IEEE Access, 5,* 3095-3110. Doi: 10.1109/ACCESS.2017.2676168

[18]. Lane N.D., Miluzzo E., Lu H, Peebles D, Choudhury T., Cambell AT (2010). A Survey of mobile phone sensing. *IEEE Communications Magazine*, *48*(9), 140-150. Doi: 10.1109/MCOM.2010.5560598.

[19]. Ortiz J.L.R., Oneto L, Monsois A.S.., Para F.A. (2015). Transition-Aware Human Activity Recognition Using Smartphones. *Neurocomputing 171,* 754-767. Doi: 10.1016/j.neucom.2015.07.085

[20]. Dai J, Bai X, Yang Z., Shen Z (2010). Mobile phone-based pervasive fall detection. *Personal and Umbiquitous Computing*, *14*, 633-643. Doi: 10.1007/s00779-010-0292-x

[21]. International Telecommunication Union (2023). Key ICT indicators for developed and developing countries, the world and special regions (totals and penetration rates). *Technical Report*, 2021.