Non-invasive diagnosis of Parkinson's disease based on skin autofluorescence spectra

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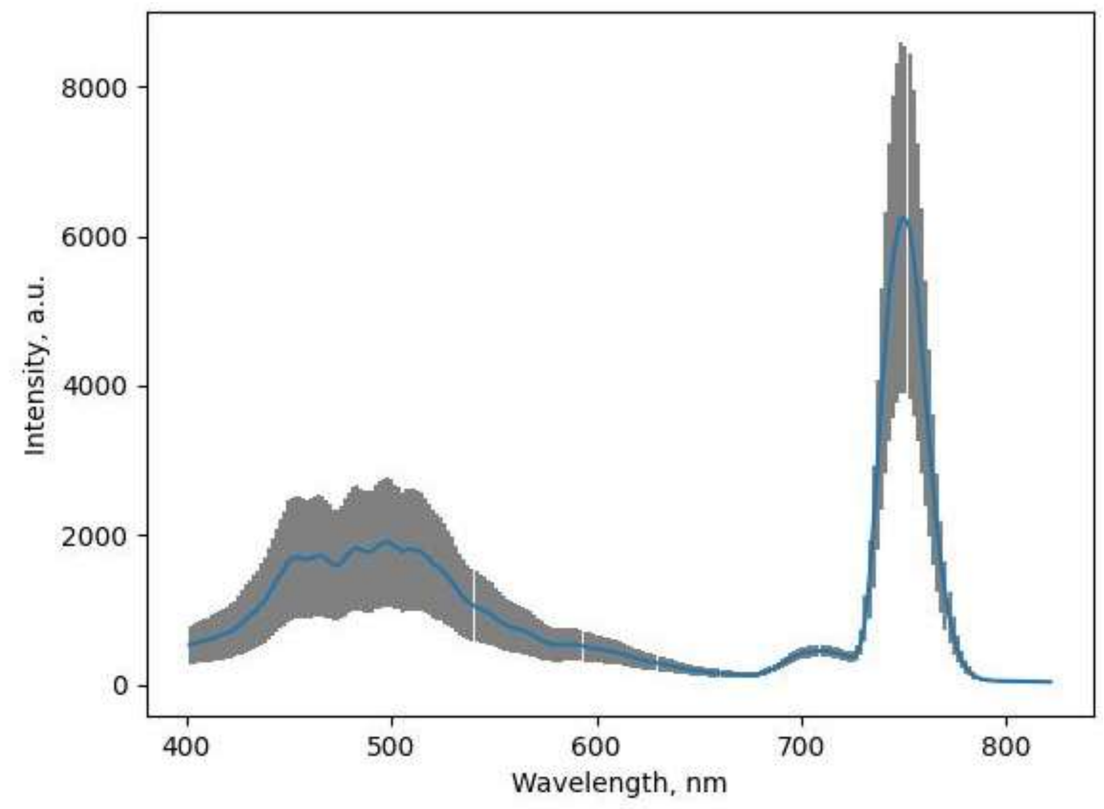
Introduction

Parkinson's disease (PD) is the second most common neurodegenerative disease, affecting approximately 1% of people over 60 years of age. Currently, there are no effective treatments for PD, but nevertheless, early diagnosis of the disease makes it possible to provide decent conditions for patients and suppress the intensity of symptoms. In this work, a method for processing and classifying the obtained skin autofluorescence spectra was developed and clinical trials were conducted. For data classification machine learning algorythms, such as gradient boosting and neural networks, were applyied.

Obtain spectral data

The experimental group included 54 people: 21 - control group of volunteers aged 50-80 years, 15 - comparison group (patients aged 50-80 years with headache, degenerative-dystrophic changes in the spine, dyscirculatory encephalopathy of both sexes), 18 - patients with PD aged 50-80 years. Exclusion criteria: decompensated diabetes mellitus, severe renal or liver failure.

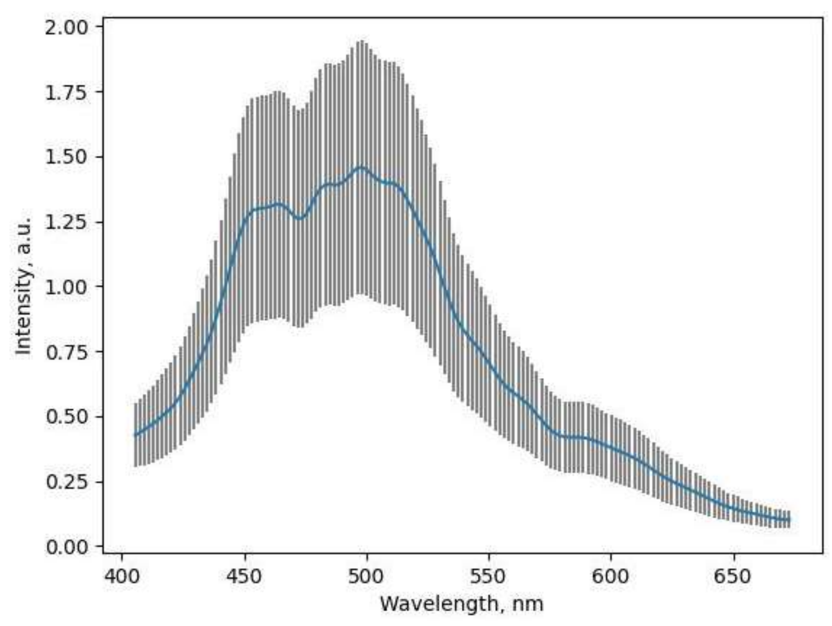
During the study, 8 autofluorescence spectra of the forearm skin surface were obtained from each patient using a spectrometer with excitation at a wavelength of 375 nm. The spectra were recorded in the range of 400-670 nm.



Raw data, obtained from patients. Blue line – average intensity, gray lines – standard deviation from average

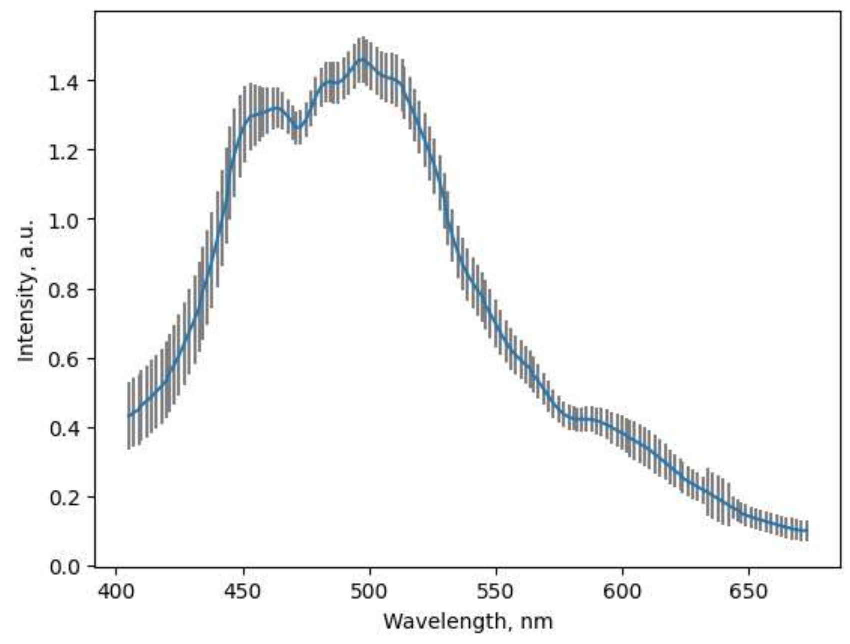
Data processing

Next, the region of interest (405-673 nm) is selected and normalized to the laser peak in the first diffraction order (~750 nm).



Normalization of the data to the laser peak (D-normalization)

To reduce dispersion, the data are renormalized as follows. The regression parameters for each spectrum are calculated using the least squares method relative to the average over all spectra. The original spectra are transformed using the coefficients found.



Normalization on the control group (I-normalization)

ML and NN model

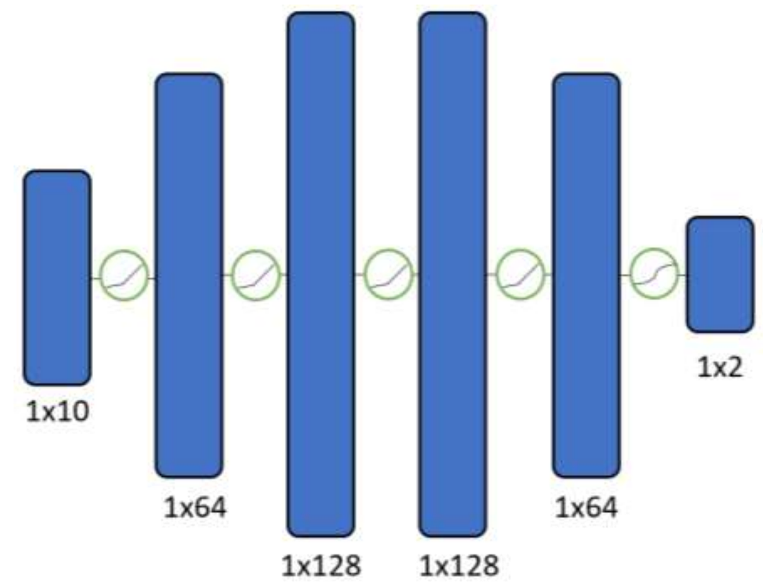
Machine learning methods and neural networks were used for classification by the presence/absence of the disease.

Primary data analysis and the use of linear classifiers as a background showed that the data are linearly bad separable. Therefore, the gradient boosting method on trees (CatBoost library, Python) and fully connected neural network models were used for classification.

To reduce computational costs and training time, 10 most informative predictors were selected using stepwise discriminant analysis. These predictors were utilized for neural network training.

Model	Number of hidden layers	Number of neurons in each hidden layer
1	3	64; 64; 64
2	3	128; 128; 128
3	4	64; 64; 64; 64
4	4	64; 128; 128; 64
5	4	128; 128; 128; 128

NN models-candidates for classification

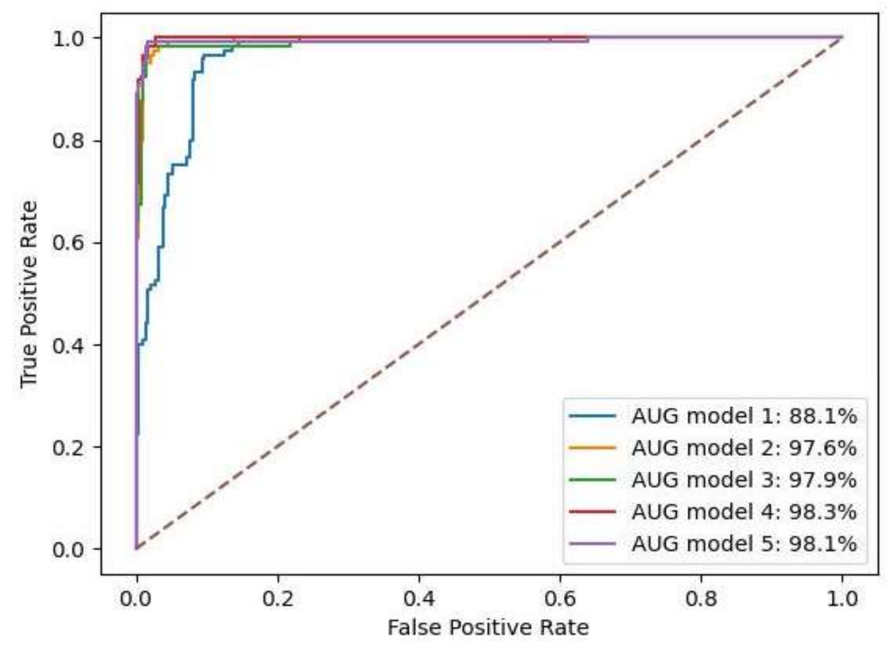


Best NN model architecture

Results

Training the CatBoost model on all predictors yielded the highest accuracy value: 98.5%
Sensetivity: 100%
Specifity: 97.6%

Training CatBoostClassifier model



ROC-AUG scores for different NN models

Training the neural network model yielded maximum accuracy of 98.1%, specificity of 99.3% and precision of 95.9%.

The ROC-AUG score was also calculated, which was 98.3% for the best model.

Despite of lower results, neural network was trained much faster, than CatBoost model (11 sec for NN model versus 90 sec for CatBoost model).

Also on inference the neural network works faster than CatBoost.

Conclusion

It has been shown that skin autofluorescence does have a predictive property in the diagnosis of Prakinson's disease. It is possible to distinguish between sick and healthy patients by spectra.

In the future, to increase the accuracy of classification, additional data such as gender, age, and biochemical parameters will be included in the consideration.