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ILMIY AXBOROTNOMA

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INTELLIGENT ALGORITHMS FOR DIAGNOSING DIABETES MELLITUS BASED ON NEURAL NETWORK MODELS

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Abstract. This study examined the effective use of modern artificial intelligence and deep learning-based neural network models, specifically MLP and TabNet models, for the early diagnosis of diabetes mellitus. The research focused on exploring efficient ways to utilize these neural network models in the early detection of the disease. In this study, TabNet and MLP models were selected and compared to automatically identify complex and nonlinear relationships in the medical dataset and to improve the effectiveness of diagnosis based on clinical indicators. The dataset underwent stages of preparation, cleaning, normalization, scaling, and feature selection through correlation analysis. The prepared dataset was split into 80% for training and 20% for testing. The methodological approach presented in this article opens up the possibility for widespread application in the automated diagnosis of other chronic and complex diseases in the future.

Keywords. AI, classification, MLP, neural network, diabetes, TabNet.

Neyron tarmoqli modellar asosida qandli diabetni tashxislashning intellektual algoritmlari

Annotatsiya. Ushbu tadqiqotda neyron tarmoq modellaridan MLP va TabNet modellaridan samarili foydalanishda qandli diabet kasalligini erta bosqichda tashxislash uchun zamonaviy sun’iy intellekt va chuqur o‘rganish asosidagi neyron tarmoq modellaridan samarali foydalanish masalasi o‘rganildi. Mazkur tadqiqotda tibbiy ma’lumotlar to‘plamidagi murakkab va nolinear bog‘liqliklarni avtomatik aniqlash va klinik ko‘rsatkichlar asosida tashxislash samaradorligini oshirish maqsadida TabNet va MLP modellari tanlab olindi, va o‘zaro taqqoslandi. Ma’lumotlar to‘plami tayyorlash, tozalash, normalizatsiya, masshtablash va xususiyatlarni tanlashda korrolyatsion bosqichlaridan o‘tkazildi. Tayyorlangan ma’lumotlar to‘plamini 80% trening va 20% test to‘plamlariga ajratildi. Ushbu maqolada keltirilgan metodologiya yondoshuvidan kelajakda boshqa surunkali va murakkab kasalliklarni avtomatlashtirilgan tarzda tashxislashda keng qo‘llash imkonini ochib beradi.

Kalit so‘zlar. AI, klassifikatsiya, MLP, neyron tarmoq, qandli diabet, TabNet.

Интеллектуальные алгоритмы диагностики сахарного диабета на основе нейросетевых моделей

Аннотация. В данном исследовании изучен вопрос эффективного использования современных моделей нейронных сетей на основе искусственного интеллекта и

глубокого обучения, в частности моделей MLP и TabNet, для ранней диагностики сахарного диабета. В данном исследовании были отобраны и сопоставлены модели TabNet и MLP с целью автоматического выявления сложных и нелинейных зависимостей в наборе медицинских данных и повышения эффективности диагностики на основе клинических показателей. Набор данных прошел этапы подготовки, очистки, нормализации, масштабирования и отбора признаков с применением корреляционного анализа. Подготовленный набор данных был разделен на обучающую (80%) и тестовую (20%) выборки. Методологический подход, представленный в данной статье, открывает возможности для широкого применения в будущем автоматизированной диагностики других хронических и сложных заболеваний.

Ключевые слова. AI, классификация, MLP, нейронная сеть, сахарный диабет, TabNet.

Introduction. Currently, artificial intelligence and machine learning technologies are beginning to be widely applied in the field of medicine. In such issues as early detection and effective diagnosis of complex and chronic diseases in the field of medicine, higher results are achieved through modern intelligent systems than traditional statistical approaches. Among medical conditions, the issue of automated diagnosis for diabetes mellitus, which is the most prevalent disease worldwide, stands out due to its urgency. Diabetes mellitus is widespread throughout the world, and its early detection and prevention are of paramount importance for the healthcare system. Early detection of diseases and recommending preventive measures and treatment to people is one of the pressing challenges of our time. In addition to traditional clinical approaches, modern machine learning models are being widely utilized in the diagnosis of diabetes mellitus. Models built on machine learning and artificial intelligence algorithms are creating the possibility to predict diseases with high accuracy based on data from existing patients[1-2]. With the advent of neural network models, new algorithms such as MLP and TabNet models are achieving high efficiency in the diagnosis of diabetes. MLP is a classic artificial neural network that allows for the study of complex linear unconnected connections. TabNet is a model optimized through deep learning of tabular data. By selecting important features using a table, it ensures the model operates with explanatory power and high precision. This research study examines the effectiveness of modern MLP and TabNet models in diagnosing diabetes mellitus. The effectiveness of these models was analyzed, results were compared, and a medical dataset was examined as part of the work carried out. This not only serves to improve the quality of diagnosis, but also expands the possibilities for automated and informed decision-making in medical practice. In recent years, due to the increasing volume and complexity of medical data, advanced machine learning models and neural network architectures have become essential tools for analyzing this information. For the early detection of diabetes mellitus, it is necessary to effectively use the processing of a large number of data collected in various formats on the clinical, laboratory, and lifestyle of patients using artificial intelligence algorithms. The need for neural network models has increased due to the inability of classical statistical models to fully capture many features and complex relationships. The main advantages of MLP and TabNet models are their self-learning and their flexibility to detect complex patterns. The MLP model studies nonlinear relationships between a large number of incoming clinical signs, and as a result, automatically identifies latent features that are important for diabetes diagnosis. The TabNet model, using a special attention mechanism, determines which column features in tabular data are most important for diagnosis, allowing the model to make interpretations and explanatory decisions. These models take into account many factors, such as age, body mass index, gender, and blood pressure, among the important characteristics of patients, when diagnosing diabetes. Each of them is a key factor in the characteristics that affect the likelihood of the disease, and the model processes these characteristics in a comprehensive manner and provides a highly accurate diagnostic result. The use of modern neural network models is of great scientific and practical importance in detecting diabetes at an early stage, assessing the risk of developing the disease, and developing appropriate preventive and treatment strategies for patients. Based on the results of this

research, it becomes possible to create automated and efficient diagnostic systems in the medical field. This will serve to widely introduce innovative approaches to the prevention and treatment of diseases in protecting the health of the population.

Literature review. Multilayer neural network (MLP), one of the neural network models, plays an important role in diabetes diagnosis. The MLP model is characterized by its efficiency in automatically learning complex features and providing high-accuracy diagnostic results[3-4]. Another modern model provides high accuracy and interpretation of tabular data analysis through a special TabNet engine. Studies show that the TabNet model provides not only diagnostic accuracy when working with medical data, but also ease of analysis and interpretation of model results [5-6]. In general, the effectiveness of modern neural network models in diabetes diagnosis has been proven in many foreign and domestic studies. Therefore, these models are widely implemented in medical information systems and show high efficiency in practice.

Methodology. This study used machine learning and deep learning models MLP and TabNet to diagnose diabetes. The methodology was implemented in stages, and the scientific basis and algorithmic sequence of each stage were organized as follows.

1. In data collection and preparation, a diabetes dataset, which is widely used in the medical field and includes clinical and laboratory indicators, was initially selected for the study. This data includes the following features. Patient age, gender, BMI, and other important clinical parameters.

2. Initial data analysis and feature selection were performed by removing unnecessary features from the dataset through column-wise correlation analysis.

3. Data partitioning randomly divided the samples from the total data set into 80% training sets and 20% test sets.

4. Building model architectures An architecture was chosen in which the MLP input layer consists of one or more hidden layers and an output layer. The number of neurons in each layer, the activation functions ReLU and sigmoid optimization algorithms Adam, and the loss function were determined. The TabNet model was used. The model extracted the most important features through dynamic attention distribution on the incoming features, and as a result, the model provided diagnostic results.

5. Model training and evaluation: For each model, optimal parameters were selected using an early stoppage of the training process and a cross-validation approach. Trained models are evaluated on the test set using the following metrics: accuracy, precision, recall, F1-score, and ROC-AUC.

Neural network algorithms. MLP is an artificial neural network architecture that consists of multiple layers, with many artificial neurons located in each layer. Unlike the classic perceptron, the MLP model has hidden layers, which allows it to study complex and nonlinear relationships. Diabetes mellitus is treated in MLP as follows.

The data loaded from the file is extracted from the table using formula (1).

$$D = \{(x^{(i)}, y^{(i)}), i = 1,2,\ldots, N\} \quad (1)$$

Here

N— number of samples, $x^{(i)} \in R^d, i -$ attributes of the sample (input feature vector), $d -$ number of attributes, $y^{(i)} -$ result (no diabetes 0 or diabetes 1).

An artificial neural network consists of several layers, each layer containing many neurons. The input layer is given by formula (2).

$$x = [x_1, x_2,\ldots, x_d]^T \quad (2)$$

Hidden layer The number of neurons n_l for each hidden layer l and the input signal $h^{(l-1)}$. It is done for each neuron by the following formula.

$$z_j^{(l)} = \sum_{k=1}^{n_{l-1}} w_{\text{jk}}^{(l)} h_k^{(l-1)} + b_j^{(l)}$$

$$h_j^{(i)} = f^{(l)}(z_j^{(l)})$$

Here

$z_j^{(l)} - l -$ in the layer $k -$ from the outside $j -$ The load on the neuron, $b_j^{(l)} - l -$ in the layer $k -$ neuron bias parameter,$f^{(l)} -$ activation function sigmoid, $h_k^{(l-1)} -$ the output signal from the previous layer. The sigmoid function for the output layer is calculated using formula (3) for the classification of whether or not there is diabetes.

$$\sigma = \sigma\left(\sum_{k=1}^{n_{L-1}} w_k^{(L)} h_k^{(L-1)} + b^{(L)}\right) \quad (3)$$

$L -$ number of layers, $\sigma(x) = \frac{1}{1+e^{-z}} -$ sigmoid activation function

If there are C classes, the softmax in the last layer is calculated using the following formula(4).

$$o_c = \frac{\exp(z_c)}{\sum \exp(z_{c\prime})} \quad (4)$$

Here z_c, $c -$ signal value of the output neuron.

The loss function is calculated using the Binary Cross-Entropy formula (5).

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y^{(i)}\log\{\hat{y}\right| \quad \left|(i) + (1 - y^{(i)})\log(1 - \hat{y}^{(i)})\right] (5)$$

Here

$y^{(i)} -$ true value (0 or 1), $\hat{y}^{(i)} -$ the value that comes out of the model's sigmoid function.

Model weights $W = \left\{w_{\text{jk}}^{(l)}\right\}$ and biases $B = \left\{b_{\text{jk}}^{(l)}\right\}$ updated in an iterative manner. It is optimized by gradient descent.

Here

$\eta -$ learning speed, $\frac{\partial L}{\partial w} -$ gradient of the loss function. Each weight measures the influence of the features on the model's output. Optimal values are determined during the training process.

TabNet this is a modern neural network architecture designed for deep learning-based analysis of tabular data. This model was proposed by Arik and Pfister in 2021, and its main innovation is that TabNet automatically performs the feature selection and feature transformation processes for each row of data using a special “attention” mechanism[7].

The TabNet architecture consists of the following main components.

- Feature transformer block: This part transforms the features in each row through a deep neural network and creates new hidden representations.
- The Attentive Transformer block uses attention to dynamically determine which features are important to the model and direct them to the next stage. As a result, a unique path is formed for each sample, making interpretation easier.

The model processes data sequentially as it passes through each layer. Through iterations, the model learns deeply about complex relationships. TabNet has the following main advantages: The model can clearly show which feature is important for each sample. Shows the best results of a deep learning model for tabular data. It is enough to train TabNet from start to finish once and the selection will be done automatically. The results of scientific research show that the TabNet model is widely used in medical diagnostics, industry, finance, and other fields[8].

The TabNet model is modeled as follows.

$D = \left\{(x^{(i)}, y^{(i)}), i = 1,2,\ldots, N\right\}$,$N -$ number of samples, $x^{(i)} \in R^d, i -$ attribute vector of the sample,

$d -$ number of attributes, $y^{(i)} -$ result (diabetes diagnosis 0 or 1).

At each stage, the model selects important parts of the features and uses only them.

a) Input input transformation $h_0 = \text{BatchNorm}(x)$

b) Create a mask feature selection mask.

For each t, a formula mask (6) is created

$$M^{(t)} = \text{sparsemax}(P^{(t)}(h_{t-1})) \quad (6)$$

$P^{(t)} -$ mask generator neural network, $M^{(t)} -$ a vector indicating the importance level (from 0 to 1) for each feature, Sparsemax – selects only the most important features, zeroing out the rest. The masked features at each stage are expressed by formula (7).

$$h_t = f^{(t)}(M^{(t)} \otimes h_{t-1}) \quad (7)$$

$f^{(t)} -$ special “feature transformer”, $\otimes -$ element-by-element multiplication operator. The results of all stages are summed and the final output is formed by (8).

$$y = \text{Aggregate}(\{h_t\}_{t=1}^{T}) \quad (8)$$

$T -$ total number of “decision steps”.

Activation and regularization TabNet uses various activation and normalization methods, such as ReLU, GLU, and BatchNorm. The following is expressed by spersemax.

$$\text{sparsemax}(z)_i = \max(z_i - \tau, 0)$$

$\tau -$ threshold ensures that the sum of all components is 1. Regularization is added to the special loss function to make TabNet "masks" sparse via the sparsity formula (9).

$$L_{\text{sparse}} = \lambda_{\text{sparse}} \sum_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} \left\| M^{(t)} \right\|_1 \quad (9)$$

Here

$\lambda_{\text{sparse}} -$ regularization coefficient for sparsity, $T -$ number of steps used in the model, $N -$ number of samples in the training batch, The mask generated for each sample in the step. The final output classification is calculated using the following formula (10).

$$\hat{y} = \sigma(W_{\text{out}} \cdot h_{\text{out}} + b_{\text{out}}) \quad (10)$$

Here

$\hat{y} -$ The final predicted classical output of the model, $\sigma -$ sigmoid activation function, $W_{\text{out}} -$ weight of the output layer, $b_{\text{out}} -$ bias parameter, $h_{\text{out}} -$ The final hidden vector from the TabNet block.

The overall loss function is calculated by the following formula (11).

$$L_{\text{total}} = L_{\text{class}} + L_{\text{sparse}} \quad (11)$$

Here

$L_{\text{class}} -$ error function between the model output and the actual result;

$L_{\text{sparse}} -$ sparse regularization loss function.

Experimental results. The research work was conducted on a dataset consisting of a total of 70,692 rows in the dataset. There are a total of 27 features in the dataset, and 1 outlier target variable, "Diabetes_Diabetes" status (0-no diabetes, 1-diabetes), was adopted. Initially, the data was cleaned, scaled, and normalized, and divided into 80% training and 20% test sets. In this study, MLP and TabNet models were tested. The experimental results are shown in Table 1, which shows the tuned values of MLP and TabNet hyperparameters. The tuning of hyperparameters has also been considered in the following research works[9].

Table 1. MLP and TabNet hyperparameters

MLP		TabNet	
Hyperparameter	Value	Hyperparameter	Value
number of layers	3	n_d	16
number of neurons	128, 64, 32	n_a	16
activation f	relu, sigmoid	n_steps	5
dropout_rate	0.3	gamma	1.5
optimizer	adam	lambda_sparse	1e-4
learning_rate	0.001	optimizer	Adam
batch_size	64	learning_rate	0.02
epochs	100	batch_size	1024
validation_split	0.15	virtual_batch_size	128
random_state	42	mask_type	sparsemax
		epochs	150

In this study, models for diagnosing diabetes mellitus were developed using MLP and TabNet neural network algorithms. The results obtained in the MLP and TabNet models are presented in Table2.

Table 2. MLP and TabNet evaluation results.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
MLP	0.9248	0.9178	0.9332	0.9254	0.98
TabNet	0.9276	0.9289	0.9260	0.9275	0.98

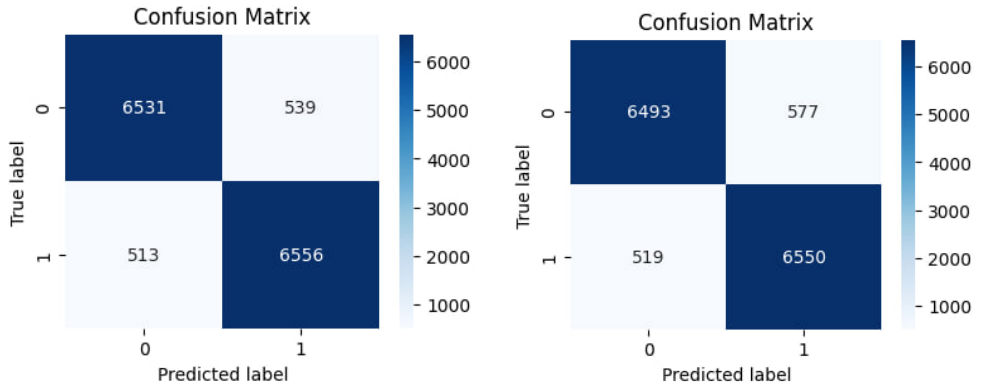


FIGURE 1. NLP and MLP confusion matrix

The confusion matrix of MLP and TabNet models is a two-dimensional matrix that shows the correct and incorrect predictions of the classification models presented in Box 1 and is an important tool in analyzing model performance. With this matrix, you can clearly see the number of samples correctly and incorrectly classified into each class. Using a confusion matrix to evaluate research results shows that it is possible to identify what errors a model makes and analyze its overall effectiveness. It can also be seen from the results of this study that the classification classes were obtained from the model in approximately equal amounts.

Conclusion. This study analyzed the effectiveness of using neural network models MLP and TabNet for diagnosing diabetes. According to the analysis of the results, it was found that neural network models have significant advantages over traditional machine learning methods. The MLP model successfully explored complex and nonlinear relationships in the data set and achieved high accuracy rates in diabetes diagnosis. The TabNet model, on the other hand, enabled automatic feature extraction using an attention mechanism and annotated presentation of diagnostic results [10-13]. At the same time, the effectiveness of all models was tested and compared based on a wide range of evaluation indicators. The results of the study show that when creating automated diagnostic systems, advanced models like TabNet provide not only accuracy, but also the ability to interpret and justify medical decisions. This will speed up the decision-making process in clinical practice, facilitate the work of doctors, and provide quality medical care for patients[14-15]. In addition, these models can be used to detect diabetes at an early stage and assess the risk of the disease in advance, thereby developing prevention and individual treatment strategies in the healthcare system. In conclusion, the methodological approach and modern models studied in this scientific work can be effectively used not only in the diagnosis of diabetes, but also in the diagnosis of many other chronic diseases. The creation of automated medical information systems based on advanced analytics and interpretive models is an important step for modern medicine.

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