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ENSEMBLING NEURAL NETWORK ARCHITECTURES FOR DIABETES PREDICTION

[1]R. Mukasheva, [1]Sh.T. Tezekpayeva✉, [2]B. Karimkyzy, [3]Ye.A. Malgazharov, [3]S.N. Kubentayeva

[1]D. Serikbayev East Kazakhstan Technical University named, Ust-Kamenogorsk, Kazakhstan,
[2]LLP «A-Medical», Almaty, Kazakhstan,
[3]S. Amanzholov East Kazakhstan University, Ust-Kamenogorsk, Kazakhstan

✉ *Corresponding author: shtezekpaeva@edu.ektu.kz*

This article discusses a neural network ensemble algorithm for clinical decision support tasks, using diabetes prediction as an example. Using an ensemble of models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, improves the accuracy and robustness of predictions compared to individual architectures. The Dirichlet Ensemble method, based on the Dirichlet distribution, is used to combine predictions. This method provides flexible and adaptive weighting of results, taking into account the confidence in each model and data uncertainty. Experiments included a comparative analysis of the models' performance, in which RNN demonstrated superior performance in terms of accuracy, recall, and F1 score. The ensemble approach improved the reliability and robustness of predictions, which is critical for clinical decision making and minimizing diagnostic errors. The study confirms the relevance of neural network ensembles and probabilistic fusion methods in medicine, contributing to the development of digital decision support systems. The practical significance of this work lies in the potential for integrating the proposed algorithm into real-world medical information systems to improve the diagnostic quality of diabetes and other chronic diseases. Further research prospects include expanding the ensemble architecture and optimizing the weights using adaptive methods.

Keywords. neural network ensembles, Dirichlet distribution, CNN, RNN, LSTM, diabetes prediction.

ҚАНТ ДИАБЕТІН БОЛЖАУ ҮШІН НЕЙРОНДЫҚ ЖЕЛІ АРХИТЕКТУРАЛАРЫН АНСАМБЛЬДЕУ

[1]Р.У. Мукашева, [1]Ш.Т. Тезекпаева✉, [2]Б. Кәрімқызы, [3]Е.А. Малгаждаров, [3]А.Н. Кубентаева

[1]«Д. Серікбаев атындағы Шығыс Қазақстан техникалық университеті» КЕАҚ, Өскемен, Қазақстан,
[2]«А-Медикал» ЖШС, Алматы, Қазақстан,
[3]«С. Аманжолов атындағы Шығыс Қазақстан университеті» КЕАҚ, Өскемен, Қазақстан,
e-mail: ShTezekpaeva@edu.ektu.kz

Мақалада қант диабетінің дамуын болжау мысалында клиникалық шешімдерді қолдау тапсырмалары үшін нейрондық желілерді ансамбльдеу алгоритмі қарастырылады. Конволюциялық нейрондық желілерді (CNN), қайталанатын нейрондық желілерді (RNN) және ұзақ мерзімді қысқа мерзімді жады (LSTM) желілерін қамтитын модельдер ансамблін пайдалану жеке архитектураларды қолданумен салыстырғанда болжамдардың дәлдігі мен тұрақтылығын арттыруға мүмкіндік береді. Болжамдарды біріктіру үшін Дирихлеттің таралуына негізделген Дирихлет ансамблі әдісі қолданылады, бұл әр модельге және деректердің белгісіздігіне сенімділікті ескере отырып, нәтижелердің икемді және бейімделгіш салмағын қамтамасыз етеді. Эксперименттер модельдердің сапасына салыстырмалы талдау жүргізді, онда RNN дәлдік, жауаптылық және F1 өлшемдері бойынша жақсы нәтижелер көрсетті. Ансамбльдік тәсіл болжамдардың сенімділігі мен тұрақтылығын жақсартты, бұл клиникалық шешімдер қабылдау және диагностикалық қателіктерді азайту үшін өте маңызды. Зерттеу шешімдерді қолдаудың цифрлық жүйелерін дамытуға ықпал ете отырып, нейрондық желі ансамбльдерін және медицинадағы ықтималдық біріктіру әдістерін қолданудың өзектілігін растайды. Жұмыстың практикалық маңыздылығы қант диабеті мен басқа да созылмалы

ауруларды диагностикалау сапасын арттыру үшін ұсынылған алгоритмді нақты медициналық ақпараттық жүйелерге біріктіру мүмкіндігінде жатыр. Әрі қарайғы зерттеулердің болашағы ансамбль архитектурасын кеңейтуді және адаптивті әдістерді қолдана отырып таразыны оңтайландыруды қамтиды.

Түйін сөздер: нейрондық желілерді ансамбльдеу, Дирихле тарату, CNN, RNN, LSTM, қант диабетін болжау.

АНСАМБЛИРОВАНИЕ АРХИТЕКТУР НЕЙРОННЫХ СЕТЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ ДИАБЕТА

[1]Р.У. Мукашева, [1]Ш.Т. Тезекпаева✉, [2]Б. Кәрімқызы, [3]Е.А. Малгаждаров, [3]А.Н. Кубентаева

[1]НАО «Восточно-Казахстанский технический университет им. Д. Серикбаева»,Усть-Каменогорск, Казахстан,
[2]ТОО «А-Медикал», Алматы, Казахстан,
[3]НАО «Восточно-Казахстанский университет им. С. Аманжолова». Усть-Каменогорск, Казахстан,
e-mail: ShTezekpaeva@edu.ektu.kz

В статье рассматривается алгоритм ансамблирования нейронных сетей для задач поддержки клинических решений на примере прогнозирования развития диабета. Использование ансамбля моделей, включающего сверточные нейронные сети (CNN), рекуррентные нейронные сети (RNN) и сети с долговременной краткосрочной памятью (LSTM), позволяет повысить точность и устойчивость предсказаний по сравнению с применением отдельных архитектур. Для объединения предсказаний применяется метод Dirichlet Ensemble, основанный на распределении Дирихле, что обеспечивает гибкое и адаптивное взвешивание результатов с учётом доверия к каждой модели и неопределённости данных. В ходе экспериментов проведён сравнительный анализ качества моделей, в котором RNN показала лучшие результаты по метрикам точности, отзывчивости и F1-меры. Ансамблевый подход улучшил надёжность и стабильность прогнозов, что критически важно для принятия клинических решений и минимизации ошибок диагностики. Исследование подтверждает актуальность применения ансамблей нейронных сетей и методов вероятностного объединения в медицине, способствуя развитию цифровых систем поддержки принятия решений. Практическая значимость работы заключается в возможности интеграции предложенного алгоритма в реальные медицинские информационные системы для повышения качества диагностики диабета и других хронических заболеваний. Перспективы дальнейших исследований включают расширение архитектур ансамбля и оптимизацию весов с использованием адаптивных методов.

Ключевые слова: ансамблирование нейронных сетей, распределение Дирихле, CNN, RNN, LSTM, прогнозирование диабета.

Introduction. The algorithm for ensemble neural network architectures in clinical decision support tasks is a method in which several different models are combined to improve the accuracy, stability, and reliability of the system [1-5]. This approach allows compensation for errors in individual networks and improving the final results by combining their predictions. In the context of clinical decisions, this is particularly important, as even minor errors in diagnosis or prognosis can have serious consequences.

The decision support system for diabetes prediction uses an ensemble that includes:

- convolutional neural networks (CNN) [6];
- recurrent neural networks (RNN) [7];
- long short-term memory (LSTM) networks [8].

The combined use of CNN, RNN, and LSTM predictions improves forecast accuracy and contributes to a more reliable determination of a patient' s likelihood of developing diabetes.

Modern medicine faces the need to improve the accuracy and reliability of clinical decisions, especially in the diagnosis of chronic diseases such as diabetes. Despite the development of machine learning and neural network methods, the accuracy

of individual models remains insufficient due to the high heterogeneity and noise of medical data. This has led to the need to find more effective approaches to information processing and disease prediction.

Ensembling neural network architecture is one of the promising areas in medical analytics, as it allows combining the advantages of different models and compensating for their weaknesses. An analysis of recent studies [1–5] shows recognition of the significance of this approach, but the use of Dirichlet distribution for optimal weighting of ensemble predictions in the context of clinical decision support has not been sufficiently studied.

The object of the study is the process of clinical decision support using machine learning methods. The subject is an algorithm for ensemble neural networks using Dirichlet distribution to improve the accuracy of diabetes prediction.

The aim of the study is to develop and test a method for ensemble neural networks (CNN, RNN, LSTM) using Dirichlet Ensemble to improve the quality of diabetes predictions.

The research objectives include:

1. analysis of existing ensemble methods in medicine;

2. development of a Dirichlet Ensemble model for combining predictions;

3. training and testing neural network models on medical data;

4. evaluation of the effectiveness of the ensemble compared to individual models.

The research methods used are machine learning, deep learning, statistical analysis, and hyperparameter optimization. It is assumed that the use of Dirichlet Ensemble will improve the accuracy and stability of forecasts by adequately accounting for uncertainty and the contribution of each model.

The theoretical significance lies in expanding the scope of ensemble methods in medical diagnostics, demonstrating the effectiveness of using Dirichlet distribution to weight predictions from different neural network architectures.

The practical significance lies in improving the accuracy and reliability of clinical decision support systems, which is especially important in the diagnosis of chronic diseases such as diabetes. The developed algorithm can be integrated into medical information systems to improve the quality of diagnosis, which helps reduce the risk of medical errors and improve patient outcomes.

In addition, the study opens prospects for further research on adaptive ensemble optimization and expanding the range of models used, which contributes to the development of personalized medicine and the digital transformation of healthcare.

Materials and methods. Within the framework of this study, the DirichletEnsemble class is used for coordinated ensemble work, which uses the Dirichlet distribution to calculate the optimal weights of models, taking into account their individual performance indicators [9]. The Dirichlet distribution is a multidimensional generalization of the beta distribution and is used to model the probabilities of several categories, such as classes in classification tasks, which allows describing the probability distribution for K classes.

Let us denote the probability for each of the K classes by $p1, p2, \dots, K$, where $p1+p2 \dots+\dots pK = 1$. The Dirichlet distribution for a K-dimensional probability vector is given by the following formula (1) [10]:

$$P\left(p_1, p_2, \dots, p_K \middle| \alpha_1, \alpha_2, \dots, \alpha_K\right) = \frac{\Gamma(\sum_{i=1}^{K} \alpha_i)}{\prod_{i=1}^{K} \Gamma(\alpha_i)} \prod_{i=1}^{K} p_i^{\alpha_i - 1} \quad (1)$$

where $\alpha 1, \alpha 2, \dots, \alpha K$ are hyperparameters, U is the gamma function, which is a generalization of the factorial.

Let there be N models, each of which predicts the probabilities of an object belonging to classes $p1, p2, \dots, pk$ for the i-model, where $i = 1, 2, \dots N$.

Using the Dirichlet Ensemble method, these predictions can be combined using a posteriori distribution, which is modeled as a Dirichlet distribution [11].

To aggregate the predictions of each model, we use the Dirichlet posterior distribution. The probabilities for each class j in the final prediction can be written as a model represented by formula (2) [12]:

$$p_j = \frac{\sum_{i=1}^{N} \alpha_i * p_{ij}}{\sum_{i=1}^{N} \alpha_i} \quad (2)$$

where: pij is the predicted probability of class j by model i, αi is the weight (or hyperparameter) that adjusts the contribution of model i to the final prediction.

The hyperparameters $\alpha 1, \alpha 2, \ldots, \alpha K$ can be updated based on the posterior distribution or through optimization methods such as gradient descent. These parameters can be interpreted as posterior confidence probabilities for each model.

The main idea is that the Dirichlet distribution generates probability distributions for classes, thereby modeling uncertainty in predictions.

Dirichlet Ensemble can be applied to medical data where there is uncertainty in the predictions of different models. For example, when classifying diagnoses based on test results, several models may give different predictions, and using the Dirichlet distribution method will allow these predictions to be combined more accurately, taking into account the uncertainty of each model and its contribution.

As shown in Figure 1, one of the steps in the algorithm for ensemble neural network architectures for clinical decision support tasks is the use of Dirichlet Ensemble to combine models.

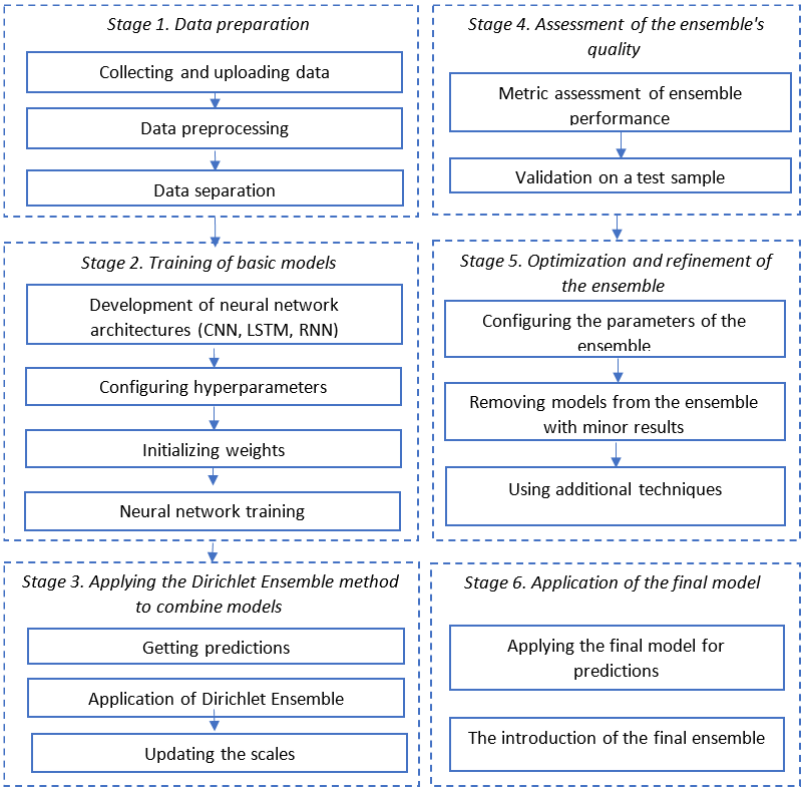


Fig.1 - Algorithm for ensemble learning of neural network architectures for clinical decision support tasks

In an ensemble of clinical decision support task classifiers, each model predicts the probability of an object belonging to a particular class. Dirichlet Ensemble combines predictions in a way that

takes uncertainty into account and distributes prediction probabilities among classes based on a posteriori distribution constructed from a Dirichlet distribution. The weights assigned to each model' s predictions are based on the Dirichlet distribution, which allows for more flexible and efficient aggregation of results.

The following advantages of ensemble learning for clinical decisions can be highlighted:

− ensemble learning reduces prediction error, as the weaknesses of one model can be compensated for by another model;

− models trained in different data subsamples or using different architectures may be more robust to noise in medical data;

− ensemble learning improves the overall reliability of predictions, which is critical for clinical decision-making, especially in life-threatening situations.

This approach makes the system more flexible and robust, which is important in the context of high uncertainty and heterogeneity of medical data.

Results and discussion. During data preparation, the samples are divided into training and test sets. The data is adapted for CNN, and the target variables are encoded using one-hot encoding. The CNN architecture includes two convolutional layers with pooling, a Flatten layer, fully connected layers with Dropout, and a softmax output for two classes. Training with categorical cross-entropy and Adam is accompanied by validation on the test sample. The results are evaluated using loss and accuracy graphs (Fig.2).

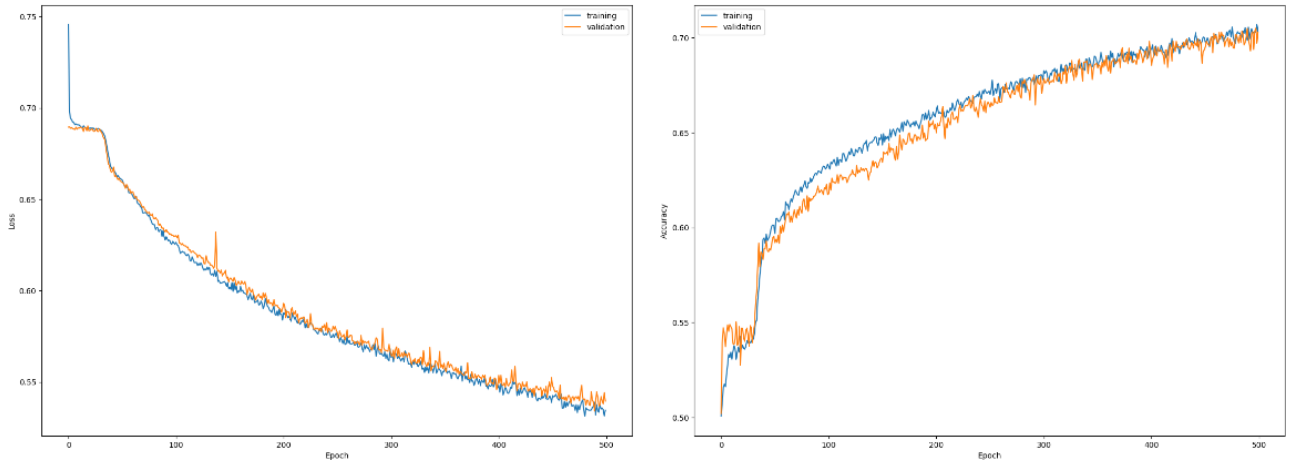


Fig.2 - Loss and accuracy graphs

CNN classification report in Table 1.

Table 1 - CNN classification report

Position	Precision	Recall	f1-score	Number of samples
False	0.66	0.82	0.73	4782
True	0.77	0.59	0.66	4800
macro avg	0.72	0.70	0.70	9582
weighted avg	0.72	0.70	0.70	9582

The CNN error matrix is represented by formula (3):

$$\begin{bmatrix} [3926\ 856] \\ [1988\ 2812] \end{bmatrix} \quad (3)$$

CNN achieved macro F1 = 0.70; instability is observed during validation.

LSTM uses input sequences of 38 steps, 50 hidden neurons, fully connected layers with ReLU and Dropout, Adam (lr=0.001), 500 epochs, batch = 512. The loss and accuracy graphs (Fig.3.37) show an increase in accuracy to ~65% without significant overfitting. Macro F1 = 0.69.

The LSTM classification report is in Table 3.9, and the error matrix is in formula (2).

Table 2 - Classification report for the LSTM model

Position	Precision	Recall	f1-score	Number of samples
False	0.67	0.74	0.70	4782
True	0.71	0.64	0.67	4800
macro avg	0.69	0.69	0.69	9582
weighted avg	0.69	0.69	0.69	9582

The LSTM error matrix is represented by formula (4):

$$\begin{bmatrix} [3521\ 1261] \\ [1725\ 3075] \end{bmatrix} \quad (4)$$

As shown in Figure 3, the accuracy graph demonstrates that both the training and validation sets show an increase, stabilizing at around 65%. This gradual increase and stabilization indicate that the model benefits from long-term training without significant overfitting, as the validation accuracy closely follows the training accuracy.

The RNN is built on SimpleRNN (50 neurons) with fully connected layers, ReLU, and softmax. Training with Adam (0.001) demonstrates a decrease in losses and an increase in accuracy (Fig.4), but with fluctuations in validation. Macro F1 = 0.73, overall accuracy — 74% (Table 3.10), better determines the False class.

The accuracy graph shown in Figure 3.38 reflects that the accuracy on the training data gradually increases, which is good for model training. However, the accuracy on the validation data, although increasing, shows some instability, which may be a sign of overfitting or insufficient generalization ability of the model.

The classification report for the RNN model is presented in Table 3.

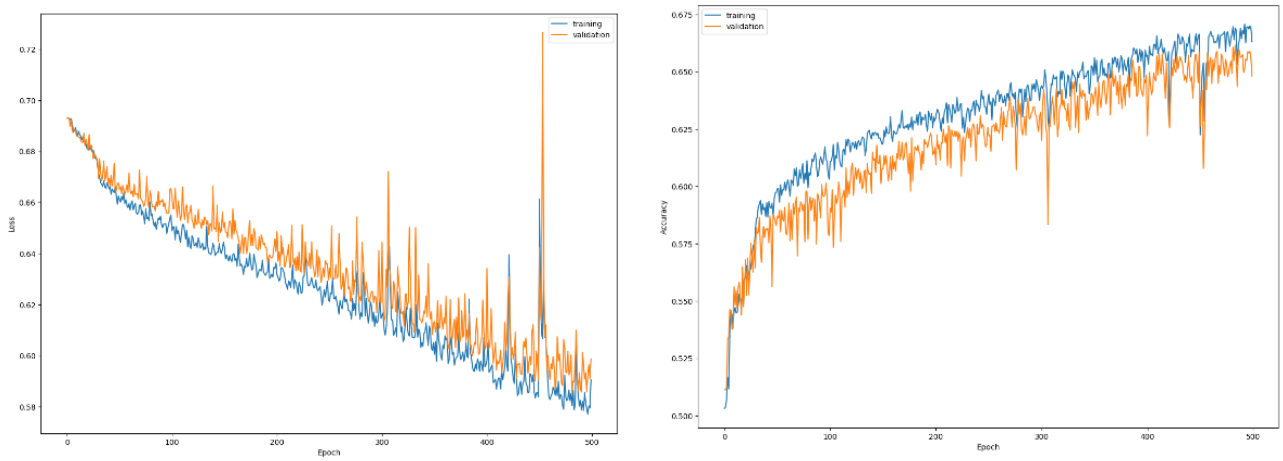


Fig.3 - Loss and accuracy graphs for the LSTM model

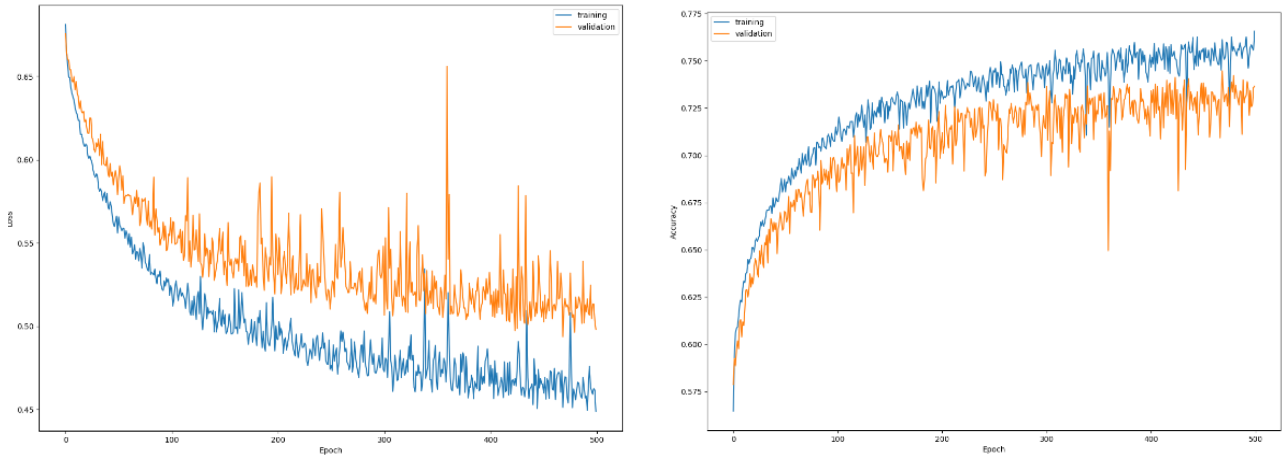


Fig.4 - Loss and accuracy graphs for the RNN model

Table 3 - Classification report for the RNN model

Position	Precision	Recall	f1-score	Number of samples
False	0.70	0.81	0.75	4782
True	0.78	0.66	0.71	4800
macro avg	0.74	0.73	0.73	9582
weighted avg	0.74	0.73	0.73	9582

The RNN error matrix is represented by formula (3.3):

$$\begin{bmatrix} [3884\ 898] \\ [1646\ 3154] \end{bmatrix} \quad (5)$$

In the study of ensemble methods (Decision Tree, AdaBoost, Random Forest, Extra Trees, Gradient Boosting), gaps were filled with medians, and cross-validation was used (Fig.5, 3.40). AdaBoost showed the highest average accuracy of 0.915, while Gradient Boosting showed the worst result.

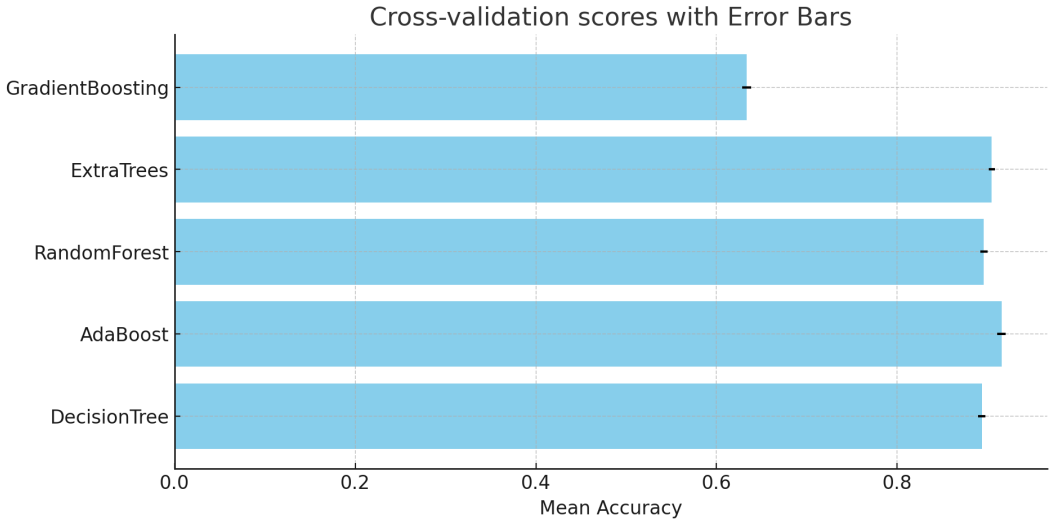


Fig.5 - Results of cross-validation of machine learning algorithms

Hyperparameter optimization using GridSearchCV and EstimatorSelectionHelper revealed GradientBoostingClassifier as the leader in terms of max_score (Fig.6).

	estimator	min_score	mean_score	max_score	std_score	learning_rate	max_depth	max_features	n_estimators
41	GradientBoostingClassifier	0.910952	0.914678	0.917058	0.00266821	NaN	9	auto	500
37	GradientBoostingClassifier	0.874507	0.876104	0.877888	0.00138689	NaN	7	auto	500
39	GradientBoostingClassifier	0.866804	0.870875	0.874319	0.0030996	NaN	9	sqrt	500
40	GradientBoostingClassifier	0.861732	0.866491	0.873943	0.00533642	NaN	9	auto	200
36	GradientBoostingClassifier	0.799361	0.809569	0.81796	0.00770064	NaN	7	auto	200
38	GradientBoostingClassifier	0.797577	0.802774	0.812324	0.00676151	NaN	9	sqrt	200
33	GradientBoostingClassifier	0.787808	0.793037	0.803119	0.00713072	NaN	5	auto	500
35	GradientBoostingClassifier	0.792316	0.79504	0.798892	0.00280016	NaN	7	sqrt	500
32	GradientBoostingClassifier	0.714071	0.723402	0.739339	0.011324	NaN	5	auto	200
34	GradientBoostingClassifier	0.724497	0.730603	0.739245	0.00628198	NaN	7	sqrt	200
31	GradientBoostingClassifier	0.70928	0.715386	0.71858	0.00431883	NaN	5	sqrt	500
29	GradientBoostingClassifier	0.677156	0.687927	0.694345	0.00766274	NaN	3	auto	500
30	GradientBoostingClassifier	0.66269	0.671301	0.681007	0.00751782	NaN	5	sqrt	200
17	RandomForestClassifier	0.664475	0.669798	0.67894	0.00649393	NaN	9	NaN	500
16	RandomForestClassifier	0.661845	0.668671	0.678753	0.00727648	NaN	9	NaN	200
28	GradientBoostingClassifier	0.646158	0.651919	0.659215	0.00543959	NaN	3	auto	200
27	GradientBoostingClassifier	0.631881	0.643653	0.652452	0.0086575	NaN	3	sqrt	500
24	ExtraTreesClassifier	0.639019	0.643966	0.652076	0.00578036	NaN	9	NaN	200
25	ExtraTreesClassifier	0.641368	0.645062	0.651418	0.00451417	NaN	9	NaN	500
15	RandomForestClassifier	0.630378	0.638111	0.649258	0.00807682	NaN	7	NaN	500
14	RandomForestClassifier	0.634135	0.639959	0.649164	0.00658507	NaN	7	NaN	200
3	DecisionTreeClassifier	0.63282	0.640522	0.645501	0.00552365	NaN	9	NaN	NaN
26	GradientBoostingClassifier	0.626245	0.630315	0.636295	0.00431974	NaN	3	sqrt	200
23	ExtraTreesClassifier	0.611497	0.619701	0.633853	0.0100495	NaN	7	NaN	500
22	ExtraTreesClassifier	0.60774	0.615662	0.628687	0.0092818	NaN	7	NaN	200
13	RandomForestClassifier	0.609243	0.616601	0.628311	0.00837079	NaN	5	NaN	500
12	RandomForestClassifier	0.605298	0.615787	0.627841	0.00926975	NaN	5	NaN	200
2	DecisionTreeClassifier	0.602574	0.609807	0.618354	0.00650916	NaN	7	NaN	NaN
9	AdaBoostClassifier	0.602386	0.60702	0.614785	0.00552489	0.1	NaN	NaN	500
10	RandomForestClassifier	0.583693	0.596374	0.611028	0.011246	NaN	3	NaN	200
21	ExtraTreesClassifier	0.590269	0.597564	0.610652	0.00927483	NaN	5	NaN	500

Fig.6 - Summary of GridSearchCV execution results

Hyperparameter optimization using GridSearchCV and EstimatorSelectionHelper revealed GradientBoostingClassifier as the leader in terms of max_score (Fig.6).

Model	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
DecisionTree	0.658347	0.641202	0.684453	0.526458	0.595148
AdaBoost	0.590222	0.585055	0.623501	0.433333	0.511308
RandomForest	0.688853	0.671467	0.696948	0.608958	0.649989
ExtraTrees	0.658481	0.643394	0.671887	0.563125	0.612717
GradientBoosting	0.958356	0.916301	0.970132	0.859375	0.911401

Fig.7 - Results of evaluating various machine learning classifiers

A comparative graph of metrics is shown in Fig.8.

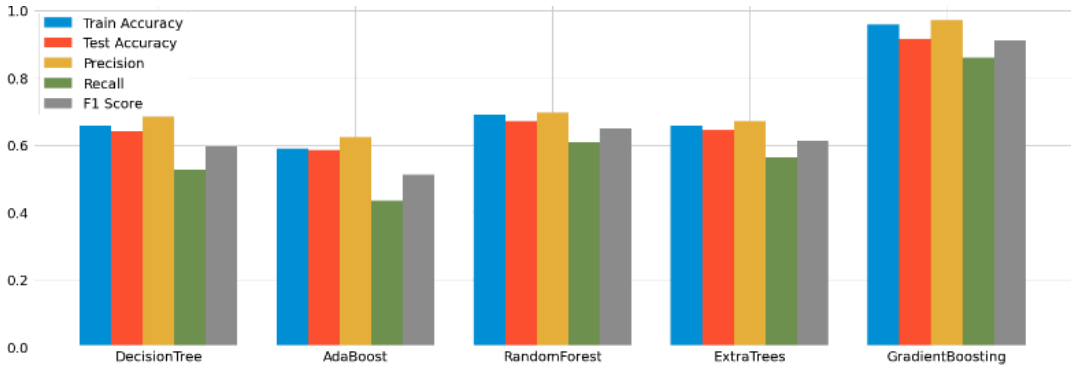


Fig.8 - Comparison chart of various quality metrics for selected machine learning algorithms

The LSTM and RNN ensemble (DirichletEnsemble) distributes weights according to ROC AUC and combines predictions. The graphs (Fig.9) show an increase in accuracy during training and fluctuations during validation.

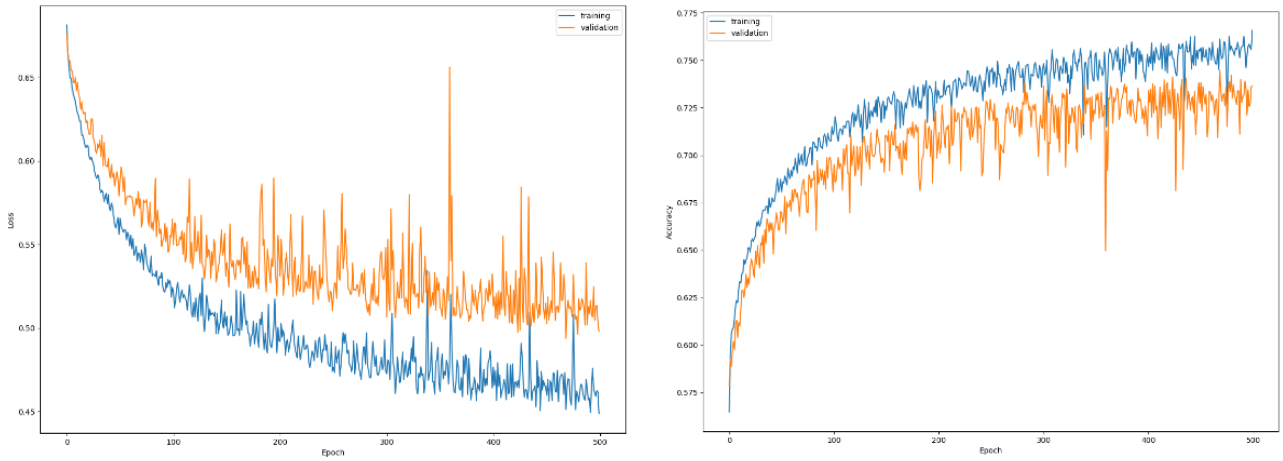


Fig.9 - Graph of losses and accuracy of ensemble training of LSTM and RNN models

Based on the results presented above, we can conclude that RNN outperformed all other models based on deep neural networks that were built. Compared to other models, RNN has the highest average accuracy, responsiveness, and f1-score, exceeding 0.74. The RNN model uses four hidden layers to maintain simplicity and increase reliability during retraining. The hidden layers use the ELU activation function along with standard kernel initializers. A sigmoid activation function is used at the output level for prediction. This approach is consistent with scientific methodology, while remaining accessible to understanding.

Conclusion. The study confirmed the effectiveness of neural network ensembles in clinical decision support tasks. Combining different architectures (CNN, RNN, LSTM) within the Dirichlet Ensemble compensated for the weaknesses of individual models and improved the accuracy of diabetes prediction. The Dirichlet distribution method provided flexible weighting of predictions, considering the confidence in each model and the uncertainty of the results.

A comparative analysis showed that among the individual architectures, RNN demonstrated the best performance (macro F1 > 0.74), which is associated with its ability to effectively process temporal dependencies in data. Among the classical ensemble algorithms, GradientBoostingClassifier demonstrated the highest accuracy.

In general, the use of ensemble strategies in medical decision support systems increases the reliability of predictions and resistance to noise, which is especially important in the diagnosis of diseases. A promising direction for further work is to expand the set of architectures in the ensemble, optimize weights using adaptive methods, and integrate the proposed system into real clinical scenarios.

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Information about authors

Mukasheva R. - Candidate of Technical Science, D. Serikbayev East Kazakhstan Technical University; Oskemen, Kazakhstan, e-mail: rmukasheva@edu.ektu.kz.

Tezekpaeva Sh. - PhD student, D. Serikbayev East Kazakhstan Technical University, Ust-Kamenogorsk, Kazakhstan, e-mail: shtezekpaeva@edu.ektu.kz;

Karimkyzy B. - master, LLP «A-Medical», Almaty, Kazakhstan, e-mail: bekzatastana@gmail.com.

Malgazharov Ye. - Candidate of Physico-Mathematical Sciences, S. Amanzholov East Kazakhstan University, Ust-Kamenogorsk, Kazakhstan, e-mail: malgazhdarov_e@mail.ru.

Kubentayeva S.– Candidate of Pedagogical Sciences, S. Amanzholov East Kazakhstan University, Ust-Kamenogorsk, Kazakhstan, e-mail: saniya_kub@mail.ru.

Сведения об авторах

Мукашева Р.У.- кандидат физико-математических наук, Восточно-Казахстанский технический университет им. Д. Серикбаева, Усть-Каменогорск, Казахстан, e-mail: rmukasheva@edu.ektu.kz;

Тезекпаева Щ.Т. - докторант, Восточно-Казахстанский технический университет им. Д. Серикбаева, Усть-Каменогорск, Казахстан, e-mail: shtezekpaeva@edu.ektu.kz;

Кәрімқызы Б. - PhD, ТОО «А-Медикал», Алматы, Казахстан, e-mail: bekzatastana@gmail.com;

Малгаждаров Е.А. – кандидиат физико-математических наук, Восточно-Казахстанский университет им. С. Аманжолова, Усть-Каменогорск, Казахстан, e-mail: malgazhdarov_e@mail.ru.

Кубентаева С.Н.- кандидиат педагогических наук, Восточно-Казахстанский университет им. С. Аманжолова, Усть-Каменогорск, Казахстан, e-mail: saniya_kub@mail.ru.