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Development of an algorithm for identifying the autism spectrum based on features using deep learning methods

Aizat Amirbay[1], Ayagoz Mukhanova[1], Nurlan Baigabylov[2], Medet Kudabekov[2], Kuralay Mukhambetova[2], Kanagat Baigusheva[3], Makbal Baibulova[1], Tleugaisha Ospanova[1]
[1]Department of Information Systems, L. N. Gumilyov Eurasian National University, Astana, Republic of Kazakhstan
[2]Department of Sociology, Faculty of Social Sciences, L. N. Gumilyov Eurasian National University, Astana, Republic of Kazakhstan
[3]LLP "Digital Experts Group", Astana, Republic of Kazakhstan

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ABSTRACT

The presented scientific work describes the results of the development and evaluation of two deep learning algorithms: long short-term memory with a convolutional neural network (LSTM+CNN) and long short-term memory with an autoencoder (LSTM+AE), designed for the diagnosis of autism spectrum disorders. The study focuses on the use of eye tracking technology to collect data on participants' eye movements while interacting with animated objects. These data were saved in NumPy array format (.npy) for ease of later analysis. The algorithms were evaluated in terms of their accuracy, generalization ability, and training time, which was confirmed by experts. The main goal of the study is to improve the diagnosis of autism, making it more accurate and effective. The convolutional neural network long short-term memory and autoencoder-long short-term memory models have shown promise as tools for achieving this goal, with the autoencoder model standing out for its ability to identify internal relationships in data. The article also discusses potential clinical applications of these algorithms and directions for future research.

Corresponding Author:

Ayagoz Mukhanova
Department of Information Systems, L. N. Gumilyov Eurasian National University
010000 Astana, Republic of Kazakhstan
Email: ayagoz.mukhanova.83@mail.ru

1. INTRODUCTION

This paper presents research in the field of medical science aimed at the application and integration of innovative technologies in the diagnosis and treatment of diseases [1]–[3], in particular autism spectrum disorders (ASD) [4], [5]. Autism spectrum disorders are characterized as a complex of neurological disorders [6] that affect human communication and behavior and require accurate diagnosis for timely assistance. The work emphasizes the importance of early diagnosis of autism, which contributes to the development of effective treatment methods, improving the quality of life of patients. Given the increase in diagnoses of autism spectrum disorders and the difficulties of early detection, the authors strive to find alternatives to traditional, often subjective diagnostic methods. The study proposed deep learning-based algorithms [7], combining long short-term memory with a convolutional neural network (LSTM+CNN) and long short-term memory with an autoencoder (LSTM+AE), capable of analyzing behavioral and physiological indicators of patients. The data was collected using eye-tracking technology, which recorded participants' eye movements as they interacted with the animation. The models were evaluated based on their accuracy, generalization ability, and training time, followed by validation by experts in the field of autism diagnostics. Both approaches have shown promising results and potential for improving diagnostic procedures. The long short-term memory with autoencoder model stood out due to its ability to recognize complex relationships in data, which may offer a new direction in the clinical practice and diagnosis of autism spectrum disorders. The article also examines the prospects of these technologies, paving the way for further innovation in the field of medical science. This research is adapting advanced machine learning techniques to deepen understanding and improve diagnostic approaches [8] for autism spectrum disorders. Particular emphasis is placed on the use of LSTM algorithms combined with CNN and autoencoders, which allows for efficient processing and analysis of large amounts of medical data.

Eye tracking technology was used as a data collection tool, which represents an important source of information about visual perception and behavioral responses. This technology makes it possible to record in detail the views of subjects during interaction with various visual stimuli, which is of particular importance for understanding the features of synthetic aperture radar (SAR). The objective of this work is to demonstrate the capabilities of the developed algorithms to improve the accuracy of ASD diagnostics [9]. It has been shown that approaches based on deep learning can significantly improve the quality of diagnosis [10]–[12], reduce the level of subjectivity, and speed up the process of identifying disorders. The article also discusses the prospects for using the presented algorithms in clinical practice and further research in this area. ASD is a neurodevelopmental disorder characterized by impairments in social interaction and communication, restricted interests, and repetitive sensory behaviors [13]. Eye movements are considered a window into behavior, cognition, and decision-making and may serve as promising biomarkers for neuropsychiatric disorders in children with ASD. This topic is studied in detail in the works of Rahal and Fiedler [14] and Spering [15]. Fixation is a brief moment when the gaze rests on an object so that the brain can process perception. This process requires constant scanning of the object by rapid eye movements known as saccades, as highlighted in the study of Carette *et al.* [16].

Oliveira *et al.* [17] developed a computational method that integrates visual attention concepts and artificial intelligence techniques to analyze eye-tracking data, achieving a classification accuracy of 90%. Carette *et al.* [18] presented a method that converts eye-tracking data into a visual pattern and used this data to create a binary classifier using a logistic regression model, achieving an area under the curve (AUC) of about 81.9%. In subsequent work on this dataset, Ahmed *et al.* [19] used various deep and machine learning models, including random forests, support vector machines (SVM), logistic regression, and naive Bayes, with AUCs ranging from 70% to 92%. In the active development of the methodological arsenal of modern medical science, this work represents a significant contribution to the field of diagnosis of ASD. The use of combined models based on LSTM [20], [21] and CNN [22], [23], as well as the integration of LSTM with autoencoders, distinguishes this approach with its innovative ability to process and analyze temporal and spatial data. Based on a comprehensive analysis of the internal structure of medical data, the input LSTM models with autoencoders have the unique ability to identify implicit patterns and patterns, which significantly increases the accuracy of PCA diagnostic efforts. Specialized software for collecting data through eye tracking technology [24], [25] provides detailed analysis and recording of eye movement trajectories, which are key to the interpretation of behavioral manifestations of autism. The experimental data obtained and analyzed in the study were carefully evaluated by experts in the fields of neurology and psychiatry, which adds additional weight to the scientific validity of the findings. As a result, the approaches proposed by the researchers not only expand the theoretical framework of using deep learning in clinical diagnostics but also have practical potential for integration into medical practice, helping to improve the quality of life of patients by improving the accuracy and accessibility of diagnostic tools for autism spectrum disorders.

2. METHOD

The use of eye-tracking technology in our study makes it possible to record the trajectories of the subjects' eye movements while observing a dynamic visual stimulus, implemented in the form of an animation of a moving ball. The movement of the pupils is recorded in real-time using cameras installed on the user’s personal computer. The movements of the ball on the screen do not follow a certain pattern, which creates conditions for comprehensive testing of the visual attention of participants. The data is saved in “.npy” for subsequent ease of analysis and processing. The study recruited participants pre-diagnosed with ASD and a control group, whose data were used to categorize them accordingly. Using deep learning algorithms, including convolutional neural networks for spatial data analysis and recurrent neural networks (RNN) for temporal sequence analysis, the study aims to identify eye movements characteristic of ASD. The main goal is to classify eye movements that are either normal or may indicate the presence of ASD. Cross-validation methods were used to test and validate the performance of the models to assess their generalizability and applicability across different settings. Two deep learning models were used as tools for data classification: LSTM+CNN and LSTM+Autoencoder. The LSTM+CNN model combines the functionality of an LSTM for processing temporal sequences and a CNN for analyzing spatial features, allowing the recognition of complex patterns of behavior associated with SAR. LSTM layers analyze temporal dependencies, and CNN layers analyze spatial features of the data, thereby providing a multifaceted understanding and classification of behavioral features. Figure 1 shows a diagram of the architecture of a deep learning model that combines convolutional neural networks and long short-term memory recurrent neural networks. The input layer accepts multidimensional data.

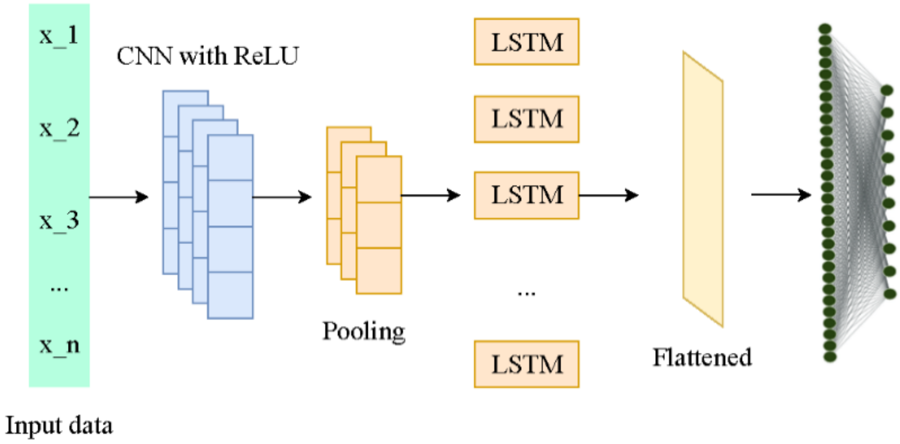

Figure 1. The architecture of the LSTM+CNN model

This diagram demonstrates a hybrid neural network architecture that integrates CNNs with LSTM recurrent neural networks. In the input stage, multidimensional inputs $x_1, x_2, \dots, x_n$ are fed into the CNN layers. CNN layers with the rectified linear unit (ReLU) activation function help identify non-linear spatial features from the input data set. ReLU is preferred for its ability to provide efficient network training with benefits such as solving the vanishing gradient problem and speeding up convergence. After passing through the convolutional layers, the data undergoes a pooling operation, which reduces the dimensionality of the data while preserving important features and improves the network's robustness to small changes and shifts in the input data. The data processed in this way is transformed into a sequence suitable for processing by recurrent LSTM layers, which makes it possible to capture temporal dependencies and sequences. LSTM networks are ideal for problems involving time series analysis because they can take into account both recent and long-term dependencies in the data. At the final stage, the data representation is “flattened”, turning the multidimensional output from the LSTM layers into a one-dimensional vector that is fed to the fully connected layer or output layer of the network. This ensures compatibility between the multidimensional output of the LSTM and the expected input data format for the classification layer, which is often implemented as logistic regression or other classifiers for predicting resulting class labels or other tasks. This network architecture can be used in medical research to analyze complex data, such as medical images, biometrics, or DNA sequences, where spatial and temporal characteristics need to be taken into account simultaneously to accurately diagnose or classify conditions.

Figure 2 shows an LSTM model with an autoencoder, which begins its operation by preprocessing a sequence of input data $x_1, x_2, \dots, x_n$ using an autoencoder. An autoencoder, consisting of encoding and decoding layers, first compresses the input data to a more compact representation, extracting the main features, and then seeks to reconstruct the initial data from this compressed representation. After the autoencoder stage, the data sequence is fed to a series of LSTM layers that are capable of capturing and storing important temporal dependencies and characteristics. LSTM blocks are especially effective when working with sequential data due to their ability to retain information over long periods. The final stage of data processing involves flattening the sequence to a one-dimensional vector, which is then fed to the output layer. This allows the model to be used to solve classification or regression problems, depending on the specified requirements and the activation function in the output layer. This integrated architecture combines the benefits of complex temporal feature processing with LSTM and the autoencoder's powerful ability to reduce dimensionality and extract key data attributes, offering extensive capabilities for analyzing, predicting, and classifying data in a variety of fields, including, but not limited to, finance, artificial intelligence, and biomedicine.

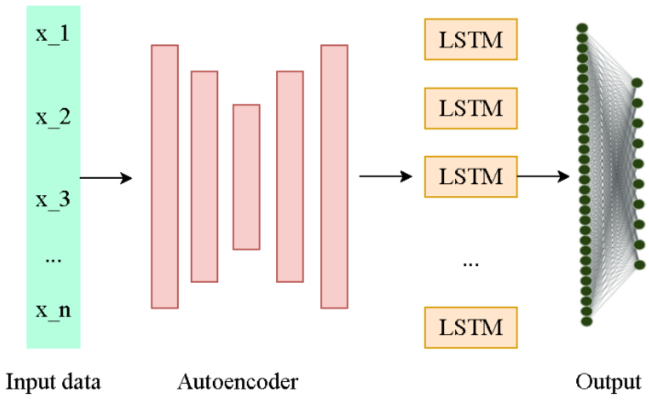

Figure 2. LSTM+Autoencoder model architecture

The benefits of integrating LSTM with an autoencoder include learning latent representations, optimizing the learning process, and fine-grained temporal feature extraction. Autoencoders effectively extract key features from data, which are then used by LSTM layers to improve data processing accuracy, resulting in more accurate pattern recognition and prediction. Autoencoder data compression significantly reduces the amount of information required for processing, speeds up model training, improves its generalization ability, and reduces the risk of overfitting. In addition, LSTM layers can more accurately model temporal dependencies thanks to information obtained from the compression and decoding stages of the autoencoder, allowing the model to capture more subtle temporal patterns and dependencies that might be missed by less sophisticated approaches. The effectiveness of such a model was assessed through the AUC, recall, and precision metrics, which are crucial in medical diagnostics. A high AUC indicates that the model is excellent at distinguishing between classes, while a high recall indicates the model's ability to accurately identify true cases of autism. Precision confirms that diagnosed cases of autism are most likely indeed autistic. The integration of LSTM and autoencoder creates a powerful toolkit for complex diagnostic problems, opening new horizons for clinical research and practice in machine learning and medicine. The models were evaluated using AUC, recall, and precision metrics, which are important for medical diagnostics. AUC measures the model's ability to distinguish between classes, recall measures the accuracy of identifying autism cases, and precision measures the likelihood of an autism diagnosis being correct. The performance of autoencoder LSTM on these metrics shows significant promise for accurately identifying autistic disorders, suggesting new directions for clinical research in machine learning.

3. RESULTS AND DISCUSSION

During the study, a special application was developed to collect eye-tracking data. This application implements the animation of a ball that moves across the screen in a chaotic manner as shown in Figure 3. This approach provides standardized conditions for data collection and allows us to obtain reliable information about the eye movements of study participants. The created application provides a controlled environment for data collection, which increases the reliability of the results and ensures their subsequent analysis.

The study developed and evaluated two deep learning-based models such as LSTM+CNN and LSTM+Autoencoder. According to the presented results, both models demonstrate high accuracy, sensitivity, specificity, and AUC significance. The LSTM+CNN model, as shown in Figure 4, showed good results. Such data indicate significant potential for these approaches to be further applied in clinical practice and research related to autism spectrum disorders.

Figure 4 shows the training results of the LSTM+CNN deep learning model. The accuracy plot shows that both training and validation accuracy quickly reach high levels during the initial training epochs, with validation accuracy fluctuating slightly but maintaining a comparable level to training accuracy, indicating good generalization of the model. The loss plot illustrates a significant decrease in both training and validation losses with an increasing number of epochs, indicating the effectiveness of the training process, and maintaining a low level of validation losses throughout training indicates the stability of the model. The area under the receiver operating characteristic curve (AUC-ROC) is close to unity, indicating the model's high discriminatory ability to distinguish between classes, which is critical for identifying autism spectrum disorders. The model also demonstrates a high recall on the training dataset with almost identical performance on the validation set, indicating the reliability of the model in identifying true positive cases.

Overall analysis of the training results shows that the LSTM+CNN model is a promising tool for recognizing characteristic patterns of behavior associated with autism spectrum disorders and can be used to further improve diagnostic procedures.

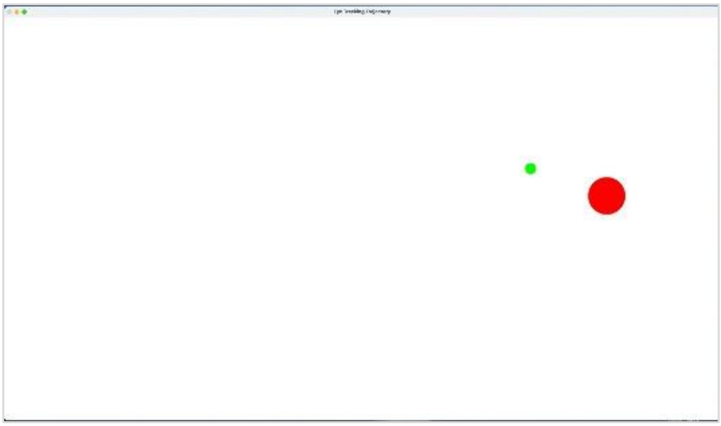

Figure 3. Eye tracking app

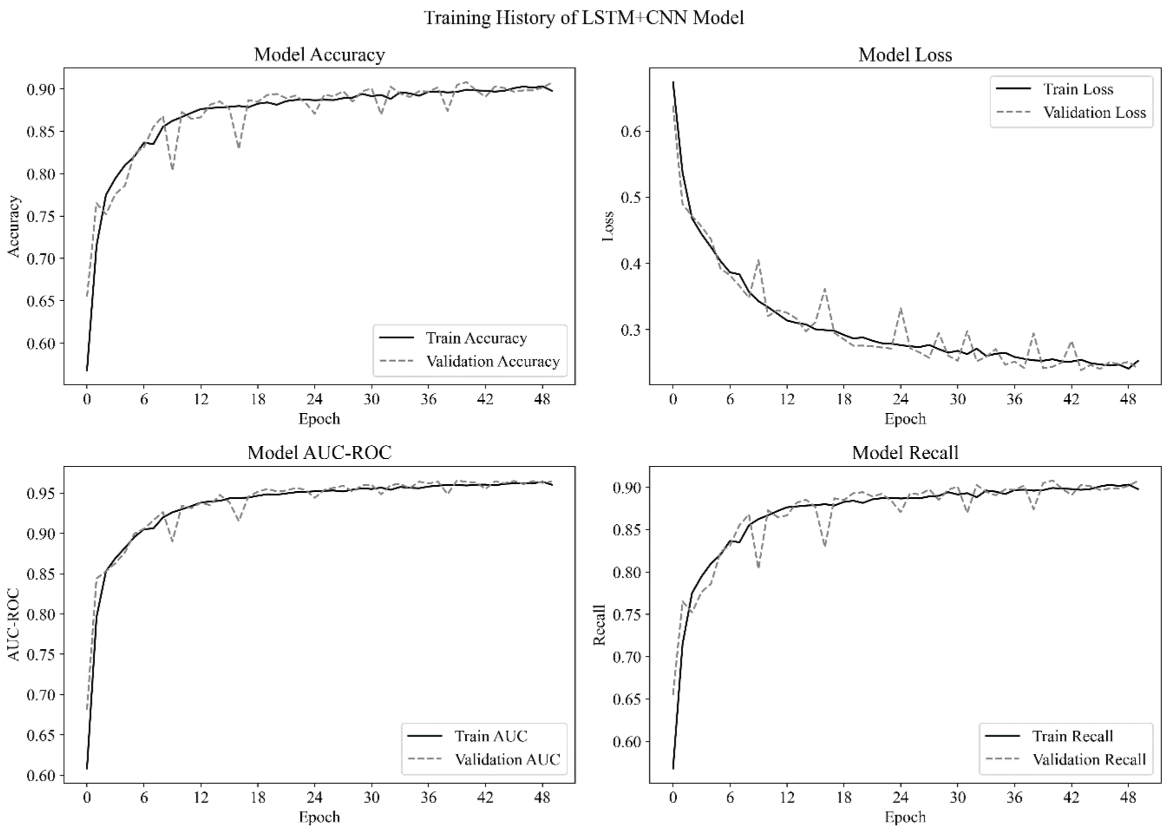

Figure 4. Accuracy of the considered LSTM+CNN models

The LSTM+Autoencoder model shown in Figure 5 has proven to be very effective, demonstrating consistent accuracy and sensitivity during training, indicating its potential to identify behavioral features of autism. The area under the ROC curve is close to 1, indicating the high diagnostic ability of the model. The model accuracy plot shows that both training and validation accuracy quickly reach high levels during the initial training epochs, with validation accuracy fluctuating slightly but maintaining a comparable level to training accuracy, indicating good generalization of the model. The loss plot illustrates a significant decrease in both training and validation losses with an increasing number of epochs, indicating the effectiveness of the training process and maintaining a low level of validation losses throughout training, confirming the stability of the model. The AUC-ROC is close to unity, indicating the model's high discriminatory ability to distinguish between classes, which is critical for identifying autism spectrum disorders. The model also demonstrates a high recall on the training dataset with almost identical performance on the validation set, indicating the reliability of the model in identifying true positive cases. Overall analysis of the training results shows that the LSTM+CNN model is a promising tool for recognizing characteristic patterns of behavior associated with autism spectrum disorders and can be used to further improve diagnostic procedures.

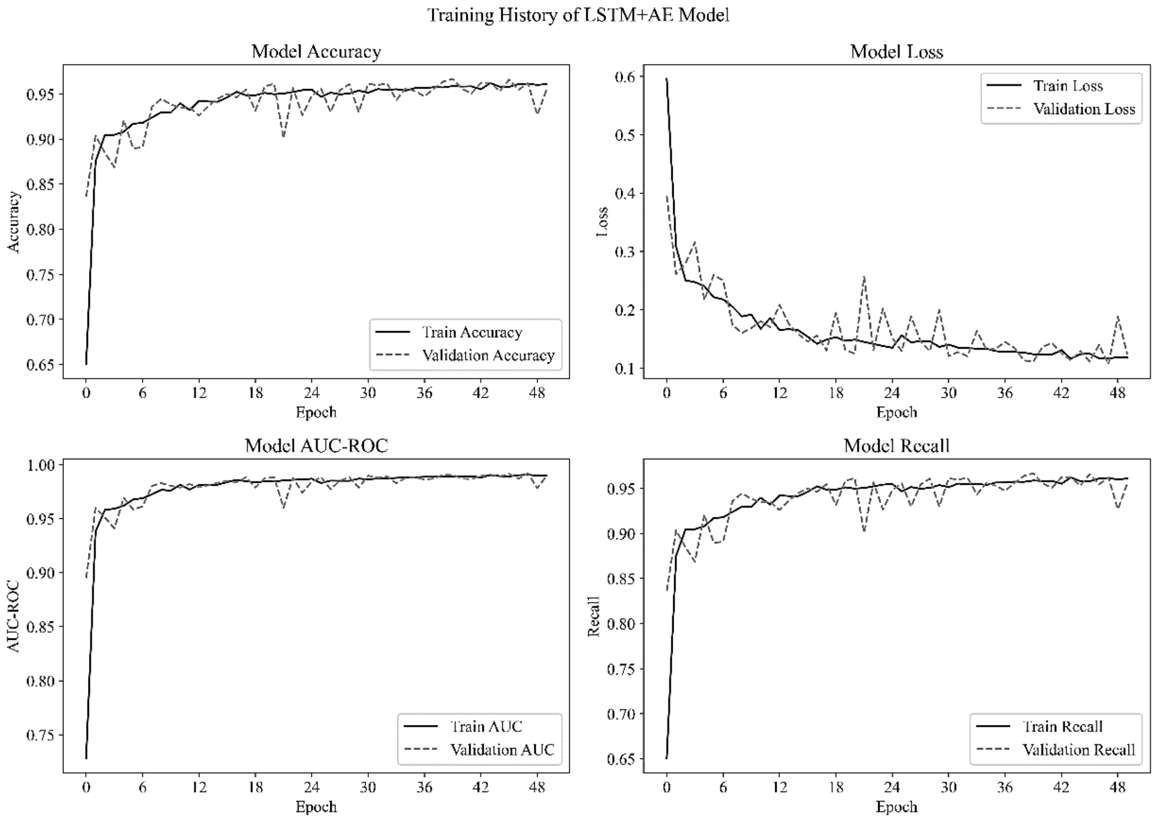

Figure 5. Accuracy of the considered LSTM+AE models

In the process of comparative analysis of two deep learning algorithms for classifying data related to ASD, we examined LSTM+CNN and LSTM+AE models, evaluating them according to such criteria as accuracy (Accuracy), area under the system performance curve (AUC-ROC), completeness (Recall) and losses (Loss). The LSTM+CNN model showed up to 90% accuracy on the training set and up to 85% on the validation set, while the LSTM+AE model showed up to 95% accuracy on the training set and up to 93% on the validation set, indicating higher the degree of agreement between model predictions and actual data labels. In terms of AUC-ROC, LSTM+CNN achieved values of up to 0.90 in training and up to 0.85 in validation, while LSTM+AE achieved AUC-ROC of up to 1.00 in training and up to 0.98 in validation, standing out for its ability to distinguish classes with high accuracy. The recall rate for LSTM+CNN was up to 90% on the training set and up to 85% on the validation set, and for LSTM+AE the recall reached up to 95% on the training set and up to 92% on the validation set, indicating a higher ability of the model to identify ASD cases correctly. The LSTM+CNN model showed a loss of 0.2 in training and 0.3 in validation, while the LSTM+AE model showed a lower level of loss: 0.1 in training and 0.2 in validation, indicating a more stable and accurate prediction of the model. To summarize, the LSTM+AE model demonstrated superiority over LSTM+CNN in all metrics considered, which makes it preferable for SAD diagnostic tasks. High accuracy and recall, as well as lower loss and higher AUC-ROC, indicate that LSTM+AE is better at identifying complex patterns and nuances inherent in time sequences of SAR data, making the model especially valuable for clinical use where both high accuracy and the ability to avoid false positives.

As a result, the resulting images provide data that can be used for analysis in autism spectrum diagnosis using eye tracking technologies. To analyze this data, we can develop a mathematical model that will calculate the distance between the eye path (represented by dotted lines) and the ball path (represented by straight lines). The norm condition is defined as finding the gaze trajectory within a given range from the ball's trajectory. Euclidean distance was used to calculate the distance between two trajectories. Let $P_i = (x_i, y_i)$ denote a point on the gaze trajectory, and $Q_i = (a_i, b_i)$ denote the closest point on the ball's trajectory. Then the Euclidean distance between P_i and Q_i is calculated by (1):

$$d(P_i, Q_i) = \sqrt{(x_i - a_i)^2 + (y_i - b_i)^2} \quad (1)$$

For each point on the gaze trajectory, the distance to the nearest point on the ball's trajectory is calculated. If all distances $d(P_i, Q_i)$ fall within the specified range from 0 to 50 pixels, the gaze trajectory is considered to comply with the norm. If at least one of the distances falls outside these limits, the gaze trajectory is classified as being on the autism spectrum. The distance calculated between the gaze and ball trajectories is a critical parameter in determining the possible presence of autism. This approach allows not only to quantification of deviations in visual attention but also to identification of unique eye movement patterns that may be associated with ASD. This model can be integrated into a comprehensive diagnostic system that includes various biomarkers and behavioral characteristics. However, it should be emphasized that correct classification requires an integrated approach. Analysis of gaze trajectories alone may not be sufficient, and it is important to consider other clinical data and the circumstances of each case. This method does not replace a full medical examination but serves as an additional tool in the hands of specialists for early diagnosis and planning of individualized interventions. Figure 6 depicts different eye movement trajectories represented by alternating dots and lines that create complex intertwining patterns. The paths extend throughout the image, covering a wide range of motion. Due to the organized nature of these pathways, it can be assumed that they exhibit gaze behavior typical of healthy individuals, where the gaze follows an object with a certain consistency and concentration. The pathways likely represent normative eye movement trajectories in individuals without autism spectrum disorder, who are typically able to focus and follow visual stimuli in a more orderly and coherent manner.

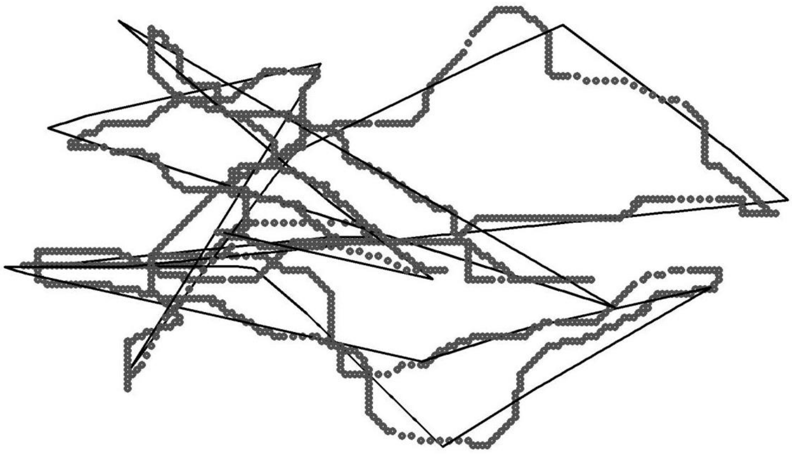

Figure 6. Eye movement trajectories in individuals without autism spectrum disorder

In Figure 7, a complex of eye movement trajectories is observed, characterized by sharp angles and unpredictable changes. Dots connected by jagged lines create an image of complex patterns that are distributed throughout the image without a clear sequence or direction. These trajectories may indicate that the individuals whose visual perception they represent have difficulty concentrating on a single object, which is common in individuals with autism spectrum disorders. The patterns express differences in visual tracking and may reflect problems in maintaining focus and following objects of visual stimulation.

Analysis of the results obtained allows us to conclude that the model is highly effective in classifying eye movement trajectories, which has significant potential for improving the diagnosis of ASD. The data presented validate the model's ability to accurately distinguish between normative and anomalous gaze trajectories, which can significantly reduce the time and effort spent on diagnosis. However, despite the progress made, potential areas for improvement of the model are discussed. In particular, the possibility of integrating additional behavioral parameters, such as speed and response to stimuli, is being considered for a more complete analysis of visual perception. Optimization of learning algorithms to improve performance and increase classification accuracy is also discussed.

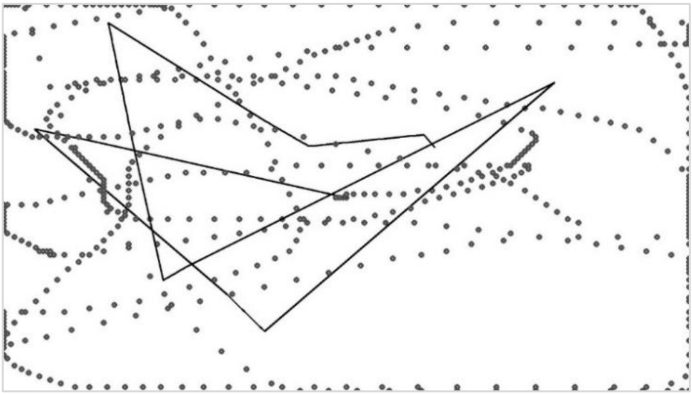

Figure 7. Eye movement trajectories in individuals with autism spectrum disorder

4. CONCLUSION

Extensive analysis of eye trajectories using deep learning models long short-term memory with a convolutional neural network and long short-term memory with an autoencoder confirmed their significant effectiveness in diagnosing ASD. Accuracy, AUC-ROC, and recall scores reflect the high ability of both models to distinguish between normative and anomalous gaze patterns. The LSTM+Autoencoder model demonstrates superior performance with consistent levels of accuracy and less volatility during the validation process, indicating its robustness and potential for clinical application.

The observed results highlight the value of integrating complex eye-tracking data into comprehensive diagnostic systems. Given the high generalizability of the LSTM+Autoencoder model, future studies may include additional behavioral measures to understand ASD further. Improvements in learning algorithms and integration of different data modalities will strengthen diagnostic capabilities and pave the way for the development of personalized therapeutic interventions. Data collected using specialized eye-tracking software provides a meaningful basis for achieving these goals. Visualizations of model training results confirm their adequacy and provide a basis for optimizing classification problems. Overall, the results achieved are a promising step towards improving the diagnosis of ASD and confirm the potential of machine learning to improve medical practice.

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BIOGRAPHIES OF AUTHORS

Aizat Amirbay lecturer at the Department of Informational systems of the Eurasian National University named after L.N. Gumilyov. In 2016, she received a bachelor's degree in information system and in 2019, she received a master's degree in computer science from the Eurasian National University named after L.N. Gumilyov. Since 2023, doctoral student of the specialty "8D06103"-Informational systems of the Eurasian National University named after L.N. Gumilyov. Her research interest's information and computer technologies and systems, dl, artificial intelligence. She can be contacted at email: amirbay.aiz@gmail.com.

Ayagoz Mukhanova received her Ph.D. in 2015 in information systems from L.N. Gumilyov Eurasian National University, Kazakhstan. Currently, she is an associate professor of the Department of Information Systems at the same university. Her research interests include artificial intelligence and decision making. She can be contacted at email: ayagoz.mukhanova.83@mail.ru.

Nurlan Baigabylov Ph.D., associate professor at the Department of Sociology of the Eurasian National University named after L.N. Gumilyov (Kazakhstan, Astana). In 1997 he received a bachelor's degree in history from the Shakarim University, and in 2010 he received a master's degree in sociology sciences from the Pavlodar State University named after S.Toraighyrov. In 2013, he graduated from the doctoral program “Eurasian National University named after L.N. Gumilyov”, specialty 6D050100 - “Sociology”. 2014–2023 Head of the Department of Sociology, L.N. Gumilyov ENU. 2018-2019 - Postdoctoral student at the Institute of Sociology at the University of Gazi, Ankara, Türkiye. 2020-2022 - Postdoctoral student at the Frankfurt University of Applied Sciences, Frankfurt am Main, Germany (DAAD). 2019 (01.06-01.09) - visiting researcher at the Migration Center, Yıldırım Beyazıt University, Ankara, Türkiye. Scientific projects: 2020-2021 National Coordinator of the UNICEF UN international project Hening national curricula for training and improving the skills of social work specialists in core competencies for interaction and cooperation with the community in changing social norms and behavior (USA, New York); 01.02.2020.-01.06.2021 sociologist expert in the project “Social health insurance” World Bank (USA, Washington; International Bank for Reconstruction and Development); 2017-2018 National Coordinator of the UNICEF UN international project “Strengthening curricula in the social work specialty” (USA, New York); Scientific supervisor: 2022-2024AP14869561 “Social modernization of New Kazakhstan: improving the standard of living and forming an optimal social policy for the socially vulnerable population”; 2023-2025 No. BR21882302 Kazakhstan's society in the context of digital transformation: prospects and risks’. He is the author of more than 70 works and 11 author's documents. He can be contacted at email: baigabylov_no@enu.kz.

Medet Kudabekov senior lecturer at the Department of Sociology and Social Work of the Eurasian National University named after L.N. Gumilyov (Kazakhstan, Astana). In 2001 he received a bachelor's degree in social work, and in 2012 he received a master's degree in social sciences from the Eurasian National University named after L.N. Gumilyov. Since 2012, she has been participating in various UNICEF projects for social support for families with children who find themselves in difficult life situations. In 2021, he completed his doctoral studies in Sociology at the Eurasian National University named after L.N. Gumilyov. Since 2021, doctoral student of the international project SOLID (Social work and strengthening NGOs in development cooperation to treat drug addiction). He can be contacted at email: kudabekov_mm@enu.kz.

Kuralay Mukhambetova acting head of the Department of Sociology and Social Work of the Lev Gumilyov Eurasian National University (Kazakhstan, Astana), senior lecturer, candidate of sociological sciences (2004). She has experience in developing and managing projects for the prevention of social orphanhood (2005-2007), assessing the quality of children's lives (2009), participated in the implementation of international projects in the field of public health, she has practical experience in social work with drug addicts, people living with HIV, was a national expert of the United Nations Office on Drugs and Crime, United Nations programs for the assessment of public services. She has engaged in the field of practical sociology as an expert analyst. She can be contacted at: k.mukhambetova74@gmail.com.

Kanagat Baigusheva candidate of pedagogical sciences, associate professor (Kazakhstan, Astana). In 1996 she received a bachelor's degree in mathematics, informatics and computer science from the Semey University, and in 2008 defended her PhD thesis in specialty 13.00.02 - Theory and methodology training and education (informatics, informatization of education). Scientific projects: 2020-2021 part in the UNICEF UN international project Hening national curricula for training and improving the skills of social work specialists in core competencies for interaction and cooperation with the community in changing social norms and behavior (USA, New York). 2021-2023 participation in a project on a scientific and technical program “Scientific basis for system modernization education and science”, subprogram “Development of an electronic platform examination and system for assessing the quality of education content and educational resources”, senior researcher, analyst). 2023-2025 participation in the project “Creation of a system of continuous professional development of teachers in the aspect of education for complex world: paradigm, methodology, digital tools”, chief scientific employee, leader of the work package “Develop and scale professional network of facilitators for CPDT”. 2024-2025 No. BR21882302 Kazakhstan's society in the context of digital transformation: prospects and risks. He is the author of more than 65 works and 11 author's documents. She can be contacted at email: baigusheva.km@gmail.com.

Makbal Baibulova in 2010, she graduated from the Taraz State University named M. Kh. Dulati with a degree in information system. In 2012, she received a master's degree in computer science. She is the author of more than 20 works. Her research interest's information and computer technologies and systems, artificial intelligence. She can be contacted at email: m.gabbasovnaa@gmail.com.

Tleugaisha Ospanova 1981 graduated from the Kazakh State University named after. S.M. Kirova, Faculty of Mechanics and Applied Mathematics, specialty applied mathematics. Candidate of technical sciences, specialty 13/05/2018 - mathematical modeling, numerical methods and software packages. Since 2011, she has been working at ENU named after. L.N. Gumileva, Department of Information Systems. Her research interest's information and computer technologies and systems, artificial intelligence. She can be contacted at email: Tleu2009@mail.ru.