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# APPLICATION OF ARTIFICIAL INTELLIGENCE IN BIOPHYSICAL SIGNAL ANALYSIS

Yorqin Sattarov
Zuhra Shonazarova
Tashkent state medical academy, Tashkent Uzbekistan

**Abstract**
This study explores the role and potential of artificial intelligence (AI) in the analysis of biophysical signals. Biophysical signals-such as heart rate, brain activity, and muscle electrical signals-are complex data derived from various physiological systems that require advanced methods for accurate and efficient interpretation. AI technologies, particularly machine learning and deep learning algorithms, demonstrate high effectiveness in the automatic detection, classification, and prediction of these signals. The application of AI enhances noise reduction, feature extraction, and early detection of pathological conditions in biophysical signals, thereby improving clinical diagnosis and treatment processes. Additionally, AI enables the processing of large-scale datasets, facilitating the development of personalized medicine and real-time monitoring systems. This research reviews the key AI algorithms used in biophysical signal analysis, their practical applications, and discusses current challenges and promising future directions in the field.

**Keywords**: artificial intelligence, biophysical signal analysis, machine learning, deep learning, physiological signals, signal processing, clinical diagnosis, pattern recognition, noise reduction, personalized medicine, real-time monitoring, biomedical engineering.

## Introduction

The rapid advancement of artificial intelligence (AI) technologies has opened new frontiers in the analysis of complex biomedical data. Among these, biophysical signals-such as electrocardiograms (ECG), electroencephalograms (EEG), electromyograms (EMG), and other physiological recordings-serve as vital indicators of the functional state of the human body. These signals are often characterized by high dimensionality, noise, and variability, which pose significant challenges for traditional analytical methods. Consequently, there is a growing need for more sophisticated computational approaches to accurately interpret and extract meaningful information from such data. Artificial intelligence, particularly through machine learning (ML) and deep learning (DL) techniques, offers powerful tools capable of learning complex patterns and relationships within large datasets without explicit programming. This ability has revolutionized biophysical signal analysis by enabling automated detection, classification, and prediction of physiological conditions with high accuracy and efficiency. AI algorithms can identify subtle signal features that may be imperceptible to human experts, facilitating early diagnosis and improved monitoring of various diseases. Moreover, AI-driven analysis supports personalized healthcare by adapting to individual variability in biophysical signals, allowing tailored interventions and real-time monitoring. Integration of AI into clinical workflows has the potential to reduce diagnostic errors, accelerate decision-making, and optimize treatment strategies, ultimately enhancing patient outcomes. This introduction aims to provide an overview of the significance of AI in biophysical signal analysis, highlighting key methodologies, their advantages over conventional techniques, and the transformative impact of AI on biomedical research and clinical practice.

The application of artificial intelligence (AI) in biophysical signal analysis holds profound significance for modern medicine and biomedical research. Biophysical signals provide essential insights into the physiological state of the body and are widely used for diagnosing and monitoring diseases. However, these signals often present challenges such as noise, variability between individuals, and complex underlying patterns that are difficult to interpret using traditional methods. AI technologies address these challenges by enabling automated, precise, and rapid analysis of large volumes of data. Machine learning and deep learning models can uncover hidden patterns, classify different signal types, and predict pathological events with high accuracy. This leads to earlier and more reliable diagnosis of conditions such as cardiac arrhythmias, neurological disorders, and muscular dysfunctions. Furthermore, AI-driven analysis facilitates personalized medicine by tailoring diagnostics and treatment plans based on individual biophysical profiles. Real-time monitoring powered by AI can provide continuous assessment of patient status, improving clinical decision-making and patient management. Overall, the integration of AI into biophysical signal analysis enhances diagnostic accuracy, reduces the burden on healthcare professionals, accelerates research discoveries, and ultimately contributes to better healthcare outcomes.

Theoretical background. Biophysical signals are time-varying electrical or mechanical signals generated by physiological processes within the body. Common examples include electrocardiograms (ECG), which record heart activity; electroencephalograms (EEG), which monitor brain waves; and electromyograms (EMG), which capture muscle electrical activity. These signals carry critical information about the functional state and health of various organ systems. The analysis of biophysical signals is inherently complex due to their nonlinear, non-stationary, and often noisy nature. Traditional signal processing techniques-such as Fourier transforms, wavelet analysis, and statistical methods-have been extensively used to extract meaningful features from these signals. However, these approaches often require manual feature engineering and may lack adaptability to signal variability caused by individual differences or pathological conditions. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), provides advanced computational frameworks that can learn directly from raw data without explicit programming. ML algorithms-including support vector machines, decision trees, and random forests-can classify signals based on extracted features, while DL models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can automatically identify hierarchical and temporal patterns from raw or minimally processed signals. These AI models improve robustness against noise and adapt to complex signal variations, enabling improved accuracy in detecting abnormalities such as arrhythmias in ECG or epileptic events in EEG. Furthermore, AI methods facilitate continuous, real-time monitoring by efficiently

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processing large datasets from wearable and implantable devices. In summary, the integration of AI into biophysical signal analysis represents a paradigm shift, allowing for automated, precise, and scalable interpretation of physiological data that supports improved diagnostics, prognostics, and personalized healthcare.

**Research Methods**

The study of applying artificial intelligence (AI) to biophysical signal analysis typically involves several key stages, combining data acquisition, preprocessing, model development, and evaluation. The following outlines the main research methods employed:

Data acquisition. Biophysical signals are collected from various sources depending on the study focus, such as ECG for cardiac monitoring, EEG for brain activity, or EMG for muscle function. Data can be obtained from publicly available databases (e.g., MIT-BIH Arrhythmia Database for ECG) or through direct recording using biomedical sensors and devices under controlled clinical or experimental conditions.

Data preprocessing. Raw signals often contain noise and artifacts from environmental interference, movement, or equipment limitations. Preprocessing steps include filtering (e.g., band-pass, notch filters), normalization, and segmentation to isolate relevant signal portions. Techniques such as wavelet transforms and empirical mode decomposition may also be used for denoising and feature enhancement.

Feature extraction and selection. Traditional AI approaches often rely on handcrafted features derived from time-domain, frequency-domain, and nonlinear analyses (e.g., heart rate variability, spectral power, entropy measures). Feature selection methods, such as principal component analysis (PCA) or recursive feature elimination (RFE), reduce dimensionality and improve model efficiency.

Model development. Machine learning models-such as support vector machines (SVM), random forests (RF), and k-nearest neighbors (k-NN)-are trained on labeled datasets to classify or predict physiological states. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can learn directly from raw or minimally processed signals, capturing complex spatial and temporal patterns.

Model training and validation. The dataset is typically split into training, validation, and testing subsets to develop and assess model performance. Techniques like k-fold cross-validation ensure robustness and generalizability. Performance metrics commonly include accuracy, sensitivity, specificity, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC).

Interpretation and deployment. Interpretability methods, such as saliency maps or SHAP values, help understand which signal features influence model decisions, increasing clinical trust. Successful models may be integrated into real-time monitoring systems or diagnostic tools to assist healthcare professionals.

Ethical considerations and data privacy. Research involving human physiological data adheres to ethical guidelines ensuring patient consent, data anonymization, and secure storage to protect privacy and comply with regulations. Through these methods, AI-based biophysical signal analysis advances the understanding and monitoring of physiological states, paving the way for enhanced diagnostic accuracy and personalized healthcare.

Findings and discussion. The application of artificial intelligence (AI) techniques in biophysical signal analysis has demonstrated significant improvements in accuracy, efficiency, and clinical relevance compared to traditional methods. Across multiple studies and experiments, AI models have shown remarkable capability in handling the complexity and variability of physiological signals.

Enhanced detection and classification accuracy: machine learning and deep learning models have achieved high accuracy rates in detecting abnormalities within biophysical signals. For instance, convolutional neural networks (CNNs) trained on electrocardiogram (ECG) data effectively classify arrhythmias with sensitivity and specificity often exceeding 90%. Similarly, recurrent neural networks (RNNs) applied to electroencephalogram (EEG) data can reliably detect epileptic seizures and other neurological events, outperforming manual analysis in speed and consistency.

Robustness to noise and variability: AI algorithms exhibit robustness against noise and inter-patient variability, which are common challenges in biophysical signal analysis. Deep learning models, by learning hierarchical features, reduce dependency on manual feature engineering and perform well even with diverse datasets collected from different populations and recording conditions.

Real-time monitoring and predictive capabilities: the integration of AI into wearable devices and continuous monitoring systems enables real-time analysis of physiological signals. This advancement supports early warning systems for acute events such as cardiac arrest or seizure onset, potentially saving lives through timely intervention. Predictive models also show promise in forecasting disease progression and treatment response, aiding personalized medicine.

Interpretability and clinical integration: despite the success in performance metrics, challenges remain regarding the interpretability of AI models. Recent developments in explainable AI (XAI) techniques help bridge this gap, allowing clinicians to understand decision-making processes, increasing trust and adoption in healthcare settings.

Limitations and future directions: while AI models offer significant advantages, they require large, high-quality labeled datasets, which can be difficult to obtain. Additionally, model generalization across different devices and patient demographics remains a challenge. Future research should focus on developing standardized datasets, improving model interpretability, and addressing ethical concerns related to data privacy.

In summary, AI-driven biophysical signal analysis represents a transformative approach that enhances diagnostic precision and patient care. Continued interdisciplinary collaboration between engineers, clinicians, and data scientists will be crucial for realizing its full potential in clinical practice.

## Discussion

The integration of artificial intelligence (AI) into biophysical signal analysis has fundamentally changed how physiological data are interpreted and utilized in healthcare. Traditional methods, while effective, often struggle with the inherent complexity and variability of signals such as ECG, EEG, and EMG. AI approaches, especially those based on machine learning and deep learning,



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provide a more adaptable and powerful framework to extract meaningful patterns from noisy and high-dimensional data. One of the most significant benefits of AI is its ability to automate the analysis process. This automation reduces reliance on expert manual interpretation, which can be time-consuming and prone to variability. AI models, once trained, can rapidly analyze large datasets, enabling continuous monitoring and faster diagnosis. This is particularly important for critical conditions like cardiac arrhythmias or epileptic seizures, where timely detection can save lives. Moreover, AI's capacity to learn complex, nonlinear relationships allows for the discovery of subtle biomarkers that may be overlooked by conventional techniques. For example, deep neural networks can identify features in ECG signals that correlate with early stages of cardiovascular diseases, potentially allowing interventions before clinical symptoms appear. Despite these advantages, challenges remain. Data quality and availability are critical issues; AI models require extensive labeled datasets for training, which are not always accessible or standardized. There is also the risk of overfitting models to specific datasets, limiting their generalizability across populations or devices. Ensuring model transparency and interpretability is another concern, as "black-box" AI systems may face resistance from clinicians who need to understand the rationale behind diagnostic decisions. Ethical and privacy considerations also demand attention. Handling sensitive physiological data necessitates stringent measures to protect patient confidentiality while enabling data sharing for research and model improvement. In conclusion, while AI offers transformative potential for biophysical signal analysis, its successful clinical integration will depend on overcoming technical, ethical, and practical challenges through ongoing interdisciplinary research and collaboration.

**Conclusion**

Artificial intelligence has emerged as a powerful tool in the analysis of biophysical signals, offering enhanced accuracy, efficiency, and the ability to handle complex physiological data beyond traditional methods. AI-driven techniques facilitate early detection, continuous monitoring, and personalized treatment by uncovering subtle patterns and adapting to individual variability. Despite challenges related to data quality, model interpretability, and ethical concerns, ongoing advancements in AI algorithms and explainability are paving the way for their broader adoption in clinical practice. Integrating AI with biophysical signal analysis holds significant promise for improving diagnostic capabilities and patient outcomes, marking a crucial step toward more precise and personalized healthcare.

**References**

1. Acharya, U. R., Faust, O., & Sree, S. V. (2017). Deep learning and artificial intelligence for biomedical signal analysis: A review. Biomedical Signal Processing and Control, 38, 44–65. https://doi.org/10.1016/j.bspc.2017.02.012
2. Faust, O., Acharya, U. R., Adeli, H., & Adeli, A. (2015). Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure, 26, 56–64. https://doi.org/10.1016/j.seizure.2015.01.003
3. Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory

electrocardiograms using a deep neural network. Nature Medicine, 25(1), 65–69. https://doi.org/10.1038/s41591-018-0268-3

4. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539
5. Шайхова, Г. И., Отажонов, И. О., & Рустамова, М. Т. (2019). Малобелковая диета для больных с хронической болезнью почек. *Экспериментальная и клиническая гастроэнтерология*, (12 (172)), 135-142.
6. Отажонов, И. О. (2010). Характеристика фактического питания и качественный анализ нутриентов в рационе питания студентов высших учебных заведений. *Врач-аспирант*, *43*(6.2), 278-285.
7. Отажонов, И. О., & Шайхова, Г. И. (2020). Фактическое питание больных с хронической болезнью почек. *Медицинские новости*, (5 (308)), 52-54.
8. Islamovna, S. G., Komildjanovich, Z. A., Otaboevich, O. I., & Fatihovich, Z. J. (2016). Characteristics of social and living conditions, the incidence of patients with CRF. *European science review*, (3-4), 142-144.
9. Отажонов, И. О. (2011). Заболеваемость студентов по материалам углубленного медосмотра студентов, обучающихся в высших учебных заведениях. Тошкент тиббиёт академияси Ахборотномаси. *Тошкент,(2)*, *122126*.
10. Гинатуллина, Е. Н., Шамансурова, Х. Ш., Элинская, О. Л., Ражапова, Н. Р., Ражабова, Н. Т., & Тожиева, З. Б. (2016). ТОКСИКОЛОГИЧЕСКАЯ ОЦЕНКА МЕДИКО-БИОЛОГИЧЕСКОЙ БЕЗОПАСНОСТИ СЫРЬЯ ДЛЯ ПРОИЗВОДСТВА НОВОГО ВИДА ПРОДУКЦИИ–БЫСТРО РАСТВОРИМОГО ЧАЙНО-МОЛОЧНОГО НАПИТКА. *Рациональное питание, пищевые добавки и биостимуляторы*, (1), 43-47.
11. Назарова, М., & Тажиева, З. (2024). ИЗУЧЕНИЕ МОРФОЛОГИЧЕСКОГО СОСТОЯНИЯ ПЕЧЕНИ ПОТОМСТВА, РОЖДЕННЫЕ В УСЛОВИЯХ ХРОНИЧЕСКОГО ТОКСИЧЕСКОГО ГЕПАТИТА У МАТЕРИ. *Journal of science-innovative research in Uzbekistan*, *2*(12), 233-240.
12. Исмоилова, З. А., Тажиева, З. Б., & Ражабова, Н. Т. COVID-19 ЎТКАЗГАН БОЛАЛАРДА ЎТКИР БУЙРАК ШИКАСТЛАНИШИНИ ҚИЁСИЙ БАҲОЛАШ. *ДОКТОР АХБОРОТНОМАСИ ВЕСТНИК ВРАЧА DOCTOR'S HERALD*, 72.
13. Rajpurkar, P., Hannun, A. Y., Haghpanahi, M., Bourn, C., & Ng, A. Y. (2017). Cardiologist-level arrhythmia detection with convolutional neural networks. arXiv preprint arXiv:1707.01836.
14. Subasi, A. (2020). EEG signal classification using wavelet transform and machine learning techniques. Biomedical Signal Processing and Control, 55, 101620. https://doi.org/10.1016/j.bspc.2019.101620
15. Zhu, T., & Liu, X. (2020). Artificial intelligence for cardiovascular medicine: Past, present and future. Frontiers in Cardiovascular Medicine, 7, 1–11. https://doi.org/10.3389/fcvm.2020.00020



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webofjournals.com/index.php/5

16. Maxsudov, V. G., Bazarbayev, M. I., Ermetov, E. Y., & Norbutayeva, M. Q. (2020). Types of physical education and the technologies of organization of matters in the modern education system. European Journal of Research and Reflection in Educational Sciences Vol, 8(9).
17. Махсудов, В. Г. (2017). Гармоник тебранишларни инновацион технологиялар асосида ўрганиш («Кейс-стади»,«Ассесмент»,«Венн диаграммаси» мисолида). Современное образование (Узбекистан), (7), 11-16.
18. Maxsudov, V. G. (2018). Improvement of the methodological basics of training of the section «Mechanical oscillations» in higher educational institutions (Doctoral dissertation, Dissertation.–Tashkent: 2018. https://scholar. google. com/citations).
19. Maxsudov, V. G. (2021). Technology of organization of modern lecture classes in higher education institutions. England: Modern views and research–2021, 160-166.
20. Матмуратов, К. Ж. (2023). Разработка методов лечения нейроишемической формы диабетической остеоартропатии при синдроме диабетической стопы.
21. Бабаджанов, Б. Д., Матмуротов, К. Ж., Моминов, А. Т., Касымов, У. К., & Атажанов, Т. Ш. (2020). Эффективность реконструктивных операций при нейроишемических язвах на фоне синдрома диабетической стопы.
22. Бабаджанов, Б. Д., Матмуротов, К. Ж., Саттаров, И. С., Атажанов, Т. Ш., & Саитов, Д. Н. (2022). *РЕКОНСТРУКТИВНЫЕ ОПЕРАЦИИ НА СТОПЕ ПОСЛЕ БАЛЛОННОЙ АНГИОПЛАСТИКИ АРТЕРИЙ НИЖНИХ КОНЕЧНОСТЕЙ НА ФОНЕ СИНДРОМА ДИАБЕТИЧЕСКОЙ СТОПЫ* (Doctoral dissertation, Rossiya. Кисловодск).
23. Бабаджанов, Б. Д., Матмуротов, К. Ж., Атажанов, Т. Ш., Саитов, Д. Н., & Рузметов, Н. А. (2022). *Эффективность селективной внутриартериальной катетерной терапии при лечении диабетической гангрены нижних конечностей* (Doctoral dissertation, Узбекистон. тошкент.).
24. Duschanbaevich, B. B., Jumaniyozovich, M. K., Saparbayevich, S. I., Abdirakhimovich, R. B., & Shavkatovich, A. T. (2023). COMBINED ENDOVASCULAR INTERVENTIONS FOR LESIONS OF THE PERIPHERAL ARTERIES OF THE LOWER EXTREMITIES ON THE BACKGROUND OF DIABETES MELLITUS. *JOURNAL OF BIOMEDICINE AND PRACTICE*, *8*(3).
25. Duschanbaevich, B. B., Jumaniyozovich, M. K., Saparbayevich, S. I., Abdirakhimovich, R. B., & Shavkatovich, A. T. (2023). COMBINED ENDOVASCULAR INTERVENTIONS FOR LESIONS OF THE PERIPHERAL ARTERIES OF THE LOWER EXTREMITIES ON THE BACKGROUND OF DIABETES MELLITUS. *JOURNAL OF BIOMEDICINE AND PRACTICE*, *8*(3).
26. Матмуротов, К., Парманов, С., Атажанов, Т., Якубов, И., & Корихонов, Д. (2023). ОСОБЕННОСТИ ЛЕЧЕНИЯ ХРОНИЧЕСКОГО ФУРУНКУЛЁЗА У БОЛЬНЫХ САХАРНЫМ ДИАБЕТОМ.
27. Abdurakhmanov, F. M., Korikhonov, D. N., Yaqubov, I. Y., Kasimov, U. K., Atakov, S. S., Okhunov, A. O., & Yarkulov, A. S. (2023). COMPETENCY-BASED APPROACH IN THE SCIENTIFIC-RESEARCH PROCESS OF HIGHER MEDICAL INSTITUTIONS'TEACHERS. *Journal of education and scientific medicine*, *1*(1), 28-31.

28. Jonson, W. S., Okhunov, A. O., Atakov, S. S., Kasimov, U. K., Sattarov, I. S., Bobokulova, S. A., ... & Boboyev, K. K. (2023). The microbiological environment of wounds and skin in patients with purulent-inflammatory diseases of soft tissues. *Journal of education and scientific medicine*, *2*(2), 72-81.
29. de Gavieres, F., Khalmatova, B. T., Okhunov, A. O., & Atakov, S. S. (2023). COMPLUTENSE UNIVERSITY OF MADRID: Impressions. *JOURNAL OF EDUCATION AND SCIENTIFIC MEDICINE*, *1*(1), 62-72.
30. Матмуротов, К. Ж., Саттаров, И. С., Атажонов, Т. Ш., & Саитов, Д. Н. (2022). Характер и частота поражения артериальных бассейнов при синдроме диабетической стопы.«. *Вестник» ТМА*, (1), 128-131.
31. Матмуротов, К. Ж., & Жанабаев, Б. Б. (2011). Влияние микобактериальных ассоциаций на кратность повторных оперативных вмешательств при диабетической гангрене нижних конечностей. *Врач-аспирант*, *46*(3.3), 394-399.
32. Babadjanov, B. D., Okhunov, A. O., Atakov, S. S., Kasimov, U. K., Sattarov, I. S., Matmuratov, K. J., ... & Korikhonov, D. N. (2023). WHY DOES SURGICAL INFECTION OFTEN AFFECT DIABETICS?: Literature review of recent data. *Journal of education and scientific medicine*, *1*(3), 66-75.
33. Bobokulova, S., Khamdamov, S., Bobobekov, A., Sattarov, I., Boboev, Q., & Abdurakhmanov, F. (2022). Treatment of acute purulent-destructive lung diseases considering the assessment of the degree of impairment of non-respiratory lung function. *JOURNAL OF EDUCATION AND SCIENTIFIC MEDICINE*, (1), 79-82.
34. Shalaeva, E., Janabaev, B., Matmurotov, Q., Kasimov, U., Pulatov, U., Bobabekov, A., & Bozorboev, M. (2016, June). 1-year clinical outcomes in patients with Parkinsonism syndrome with/without type 2 diabetes. In *MOVEMENT DISORDERS* (Vol. 31, pp. S62-S63). 111 RIVER ST, HOBOKEN 07030-5774, NJ USA: WILEY-BLACKWELL.
35. Shalaeva, E., Saner, H., Babadjanov, B., Pulatov, U., Matmurotov, Q., & Shalaeva, A. (2015, August). Prognostic value of coronary artery calcium score for major perioperative cardiovascular complications in type 2 diabetic patients undergoing trans-femoral amputation. In *EUROPEAN HEART JOURNAL* (Vol. 36, pp. 928-928). GREAT CLARENDON ST, OXFORD OX2 6DP, ENGLAND: OXFORD UNIV PRESS.
36. Атажанов, Т. Ш., Бабаджнаов, Б. Д., Матмуротов, К. Ж., & Саттаров, И. С. Анализ эффективности малоинвазивных методов в лечении диабетической гангрены нижних конечностей. *Раны и раневые инфекции*, 20-21.
37. Shalaeva, E., Janabaev, B., Babadjanov, B., Matmurotov, Q., Kasimov, U., Pulatov, U., & Bobabekov, A. (2016). Severity of coronary artery stenosis in patients with critical peripheral artery disease undergoing high amputation. *Atherosclerosis*, *252*, e141-e142.
38. Shalaeva, E., Janabaev, B., Matmurotov, Q., Kasimov, U., Pulatov, U., & Bobabekov, A. (2016). Severity of atherosclerotic lesions and foot synovial tendon complex injury as factors of sepsis development in patients with diabetic foot. *Atherosclerosis*, *252*, e137-e138.
39. Бабаджанов, Б. Д., Матмуротов, К. Ж., Моминов, А. Т., Бабабеков, А. Р., Атаков, С. С., & Атажанов, Т. Ш. (2015). Эффективность внутриартериального введения флуконазола




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webofjournals.com/index.php/5

при лечении осложненных форм диабетической стопы. *ООО «Maxliyo-shifo» &*, *2014*, 28-30.

40. Babadjanov, B. D., & Matmurotov, K. J. (2019). Efficacy of minimally invasive procedures in the treatment of lower extremities diabetic gangrene. *European science review*, *2*(1-2), 79-82.
41. Матмуротов, К. Ж., & Жанабаев, Б. Б. (2011). Влияние микобактериальных ассоциаций на кратность повторных оперативных вмешательств при диабетической гангрене нижних конечностей. *Врач-аспирант*, *46*(3.3), 394-399.





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