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Review Paper

ARTIFICIAL INTELLIGENCE IN THE BIOCHEMICAL LABORATORY - IMPACT ON DIAGNOSTICS

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Abstract. *The application of artificial intelligence (AI) in medical laboratories has influenced the change in the work of diagnostic laboratories. AI leads to workflow optimization and affects laboratory operational efficiency. This review provides an overview of the latest research in the field of AI application in biochemical laboratories. An overview of peer-reviewed papers referenced in several databases (Science Direct, PubMed, Scopus, Research Gate and Google Scholar) published between 2020 and 2025 was performed. The research was performed based on keywords connecting AI and diagnostic laboratories. This paper begins with a brief overview of AI and AI models currently used in medical and health laboratories. After that, the existing challenges of the AI model, possible solutions and their application were explained, and finally an insight into the possibilities of applying AI in the future was given. In recent years, significant progress has been made in the development of AI applications in biochemical and clinical chemistry laboratories. This trend is expected to accelerate in the coming years. AI significantly improves many processes in the laboratory. Existing applications are related to workflow automation, biomarker data analysis, real-time results processing, easier decision-making by clinical staff, etc. However, there are also issues that require caution when incorporating AI into laboratory practice. They relate to concern for data integrity, potential biases about used algorithms and certain ethical issues. Laboratories are ready for greater automation and incorporation of AI and IoT technologies in the future. Existing applications affect the performance of all phases of analysis in chemical and biochemical diagnostic laboratories. Although the application of AI in laboratory diagnostics represents the potential for improving the accuracy of results and efficiency of work, and improving health care outcomes, it is necessary to answer some ethical questions and change the legal framework for solving issues related to data privacy and the responsibility of algorithms.*

Key words*: Artificial intelligence, AI, Biochemical laboratory, Diagnostic laboratory*

Introduction

In this paper, the term medical laboratory/clinical laboratory is considered in accordance with the definition of the BAS EN ISO 15189:2023 Standard, which is identical to the EN ISO 15189:2022 standard [1] "a laboratory for biological, microbiological, immunological, chemical, immunohematological, hematological, biophysical, cytological, pathological, genetic, or other examinations of material obtained from the human body for the purpose of obtaining information for the diagnosis, monitoring, prevention, and treatment of disease or for the assessment of human health, which may provide a consulting advisory service covering all aspects of laboratory testing, including interpretation of results and advice on further appropriate examinations" [1]. Instead of this term, in practice a broader term is very often used – laboratory medicine. The primary role of this laboratory is to conduct analyses or tests for the purpose of providing a diagnosis, which is why the term diagnostic laboratories is often used. The results of the conducted tests are mostly used during the establishment of diagnosis and treatment of hospital patients, hence the term clinical laboratory is also in use. Laboratories of this type are required to apply the Principles of Good Laboratory Practice [1, 2, 3, 4] and be accredited by the competent accreditation body in accordance with ISO 15189 and/or ISO 17025 [5]. Depending on the purpose and type of examination, medical laboratories are organized as chemical, biochemical, microbiological, pathological, and other laboratories.

Many aspects of laboratory work have long been digitalized, numerous procedures have been automated, and electronic reporting and digital transmission of results have been in use for quite some time [6]. Laboratory test results, which encompass various types of tests and analyses, represent highly sensitive diagnostic information, the quality of which may be compromised in different ways. The expansion of the application of information and communication technologies (ICT), including the use of the Internet of Things (IoT) and artificial intelligence (AI), can significantly reduce errors that jeopardize result quality, contribute to the automation of the entire testing process, and reduce the workload of laboratory personnel [7]. A large amount of data (test results and quality control data) generated during measurements is stored in databases managed by laboratory staff. Although progress in digital transformation is evident, many areas within laboratories have yet to fully embrace contemporary advances in data science, including artificial intelligence and machine learning [8].

Artificial intelligence (AI) is a rapidly developing technology that provides extensive capacity for data storage and the development of complex algorithms [9]. AI holds great potential for application in various fields, and in recent years, increasing attention has been devoted to its application in medical laboratories.

Artificial intelligence (AI) is poised to bring about revolutionary changes in the healthcare system by seamlessly integrating with existing healthcare infrastructures [10]. In recent years, laboratories have transformed from primarily manual operations into highly automated systems. These transformed laboratories generate vast quantities of test results on a daily basis. The volume of data obtained far exceeds the capacity of the human brain to process. In the next stage of the development of medical laboratories, the application of AI is inevitable [11].

AI enables computers to emulate human intelligence with minimal human intervention [12, 13]. Advances in mobile technology, the Internet of Things (IoT), and data security further accelerate the adoption of AI in numerous healthcare delivery models [14]. A substantial body of research has been published in the scientific literature demonstrating that AI models can be applied in various phases of the laboratory testing process. However, to date, only a limited number of commercial AI-based products are available for practical application in medical laboratories [15].

AI technology in healthcare is based on machine learning (ML) and non-ML methodologies. Machine learning, a subset of AI, employs algorithms to analyze datasets (e.g., detection and classification), enabling the autonomous recognition of patterns across different domains. In contrast, non-ML approaches rely on deterministic models and traditional statistical methods, focusing on analysis and prediction without the use of adaptive algorithms [12].

Machine learning (ML) involves the construction of adaptive models that learn from experience. These models can automatically perform specific tasks by processing datasets through complex algorithms. ML can further be divided into three types: supervised learning, unsupervised learning, and reinforcement learning [12, 16]. The majority of AI models currently applied in diagnostic laboratories are based on supervised learning [9]. Deep learning (DL), a subset of ML, simulates the human brain in order to establish artificial neural networks (ANN). ANNs perform functions similar to those of the human brain, allowing algorithms to learn from and analyze large datasets [17]. Both DL and ML algorithms have applications in medical diagnostic and clinical laboratories, with the choice of algorithm depending on the specific context.

The application of AI in medical laboratories provides opportunities for improving the accuracy of results and operational efficiency. By employing AI-driven automation, laboratories can optimize workflows, thereby minimizing human error and strengthening support for diagnostic decision-making, achieving healthcare objectives, improving patient outcomes, and reducing costs [8].

This paper provides an overview of contemporary research related to the application of AI models in medical laboratories and presents some new ideas that contribute to the development of intelligent laboratories. This paper analyzes the transformative role of AI in the medical-biochemical laboratory, emphasizing its importance, applications, and implications for the future of diagnostics in healthcare and medicine.

Materials and Methods

A review was conducted of peer-reviewed articles indexed in multiple databases (ScienceDirect, PubMed, Scopus, ResearchGate, and Google Scholar) published between 2020 and 2025. The search was performed using keywords linking AI and diagnostic laboratories: *“Artificial intelligence in medical laboratories,” “Artificial intelligence in laboratory diagnostics,” “Artificial intelligence in clinical* *laboratories," "Artificial intelligence in biochemistry,"* and *"Artificial intelligence in chemistry."* The analysis included articles published in leading scientific journals in the fields of computer and information sciences, medical and health sciences, as well as the natural sciences (chemistry, biochemistry, and biology), which contribute to the advancement of diagnostic methods and the improvement of laboratory efficiency. In this review, the selected articles were categorized into three domains: the impact of AI on the pre-analytical phase, the impact of AI on the analytical phase, and the impact of AI on the post-analytical phase of testing in the medical-biochemical laboratory.

Results and Discussion

Artificial intelligence has the potential to enhance laboratory workflows and the interpretation of analytical data. By improving efficiency, accuracy, and predictive capabilities, AI is revolutionizing operations in biochemical laboratories. Given the increasing complexity of data generated in biochemical laboratories, the adoption of AI tools has become essential [8, 18].

Artificial Intelligence in Chemical and Biochemical Laboratories

Through the application of machine learning and deep learning techniques, artificial intelligence substantially enhances the accuracy, speed, and efficiency of diagnostics, while streamlining laboratory workflows across all stages of testing in biochemical laboratories, including the pre-analytical, analytical, and post-analytical phases [19].

Ashraf et al. (2025) [8] emphasize a range of benefits associated with the integration of AI throughout the entire laboratory testing process. Several machine learning models have already been implemented at different stages of laboratory testing (Figure 1).

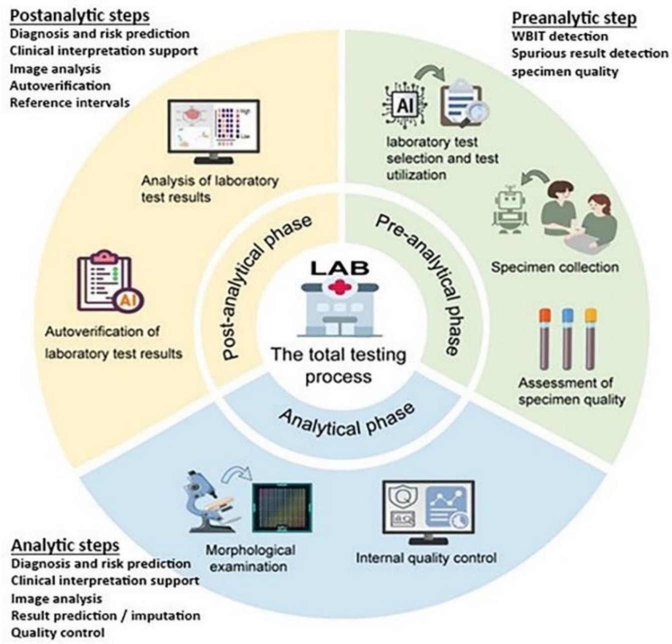

Figure 1. Application of machine learning in the clinical laboratory (Adapted from [9, 20]).

The pre-analytical phase encompasses multiple steps, many of which are often outside the direct supervision of the laboratory, thereby creating a high potential for errors that may compromise the accuracy of patient sample collection and sample preparation for analysis. Through workflow automation and enhanced communication between healthcare providers and laboratories, AI improves monitoring and error detection. Ultimately, this contributes to greater reliability of testing and the minimization of pre-analytical errors [8].

In recent years, automated recommendation systems for laboratory testing have been introduced. Yu et al. (2020) [21] developed a deep learning (DL)-based recommendation model that can assist clinicians in selecting appropriate tests. Azarkhish et al. (2012) [22] designed a neural network model for predicting iron deficiency anemia and serum iron solubility based on data derived from four routine laboratory tests (MCV, MCH, MCHC, Hb/RBC).

Furthermore, DL algorithms can be applied to robotic systems for venous blood collection [23].

A substantial proportion of testing errors arise during the pre-analytical phase. One particularly concerning pre-analytical error in the medical laboratory is the occurrence of “wrong blood in tube” (WBIT), in which a blood sample collected from one patient is erroneously labeled as belonging to another. This type of error is difficult to detect within the laboratory. Several studies have demonstrated that ML models exhibit strong performance in identifying WBIT errors [24].

Analytical Phase. AI enhances the analytical phase by enabling more advanced processing of complex biomarker data, which are crucial for diagnosing many diseases. Traditional biomarker interpretation is time-consuming and prone to error due to the sheer volume of data. AI-driven models can analyze data in real time, detecting disease indicators (e.g., proteins or genetic anomalies) before clinical symptoms manifest. This allows for timely intervention and improved patient outcomes [8].

Alongside the automation of laboratory testing, digital imaging technologies can be implemented in biochemical laboratories. Recent studies have evaluated the potential of AI/ML to optimize workflows related to sample processing, pre-analytical error detection, and clinical decision support in tests that require visual inspection. Some platforms now offer digital imaging of samples to assess color shade variations, which can be used to identify pre-analytical error sources, such as hemolysis [25].

Serum protein electrophoresis (SPEP) is a valuable tool for detecting severe serum protein disorders. The interpretation of SPEP requires extensive training of analysts and clinicians, involving careful pattern recognition and expert alignment to identify possible variations. In the future, ML could serve as a valuable tool for improving interpretation. A recent study by Chabrune et al. (2021) [26] demonstrated the potential for developing an effective tool to support the clinical interpretation of SPEP results. LC-MS/MS is the most widely used LC-MS system currently applied in biochemical medical laboratories. Data review in LC-MS/MS is managed either through expert system–based rules or via manual review following rule-based expert frameworks [20].

Morphological examination remains the gold standard for diagnosing many diseases and represents one of the main areas where ML models are applied in medical (clinical) laboratories. However, the application of ML in blood morphology examination remains limited. Only a few automated digital morphology analyzers based on ML are currently in clinical use for blood smear evaluation [16].

Kimura et al. (2019) [27] developed an automated diagnostic system for myelodysplastic syndrome, designed to distinguish myelodysplastic syndrome from aplastic anemia. The system consists of a peripheral blood smear analysis module based on a convolutional neural network (CNN) and a decision-making system utilizing extreme gradient boosting.

Automated urine sediment analyzers currently used in clinical practice are based on two principles: one relies on flow cytometry, while the other employs automated microscopic image analysis. The latter group of instruments for urine microscopic image processing utilizes certain traditional ML algorithms [9]. Due to the complexity of urinary formed elements, precise segmentation of target particles using these conventional ML algorithms is highly challenging, which can lead to poor feature extraction quality. Consequently, ML-based automated urine sediment analyzers struggle to achieve highly accurate urine sediment analysis. Several researchers have begun exploring the use of DL algorithms—particularly convolutional neural networks (CNNs)—for urine sediment analysis, as these models can directly learn features from manually annotated images [28].

Internal quality control (IQC) is the standard approach for evaluating the stability of testing methods. Zhou et al. (2022a) [29] established a patient-based real-time machine learning IQC method (MLiQC). Using a random forest (RF) algorithm, they compared the performance of the novel approach with the classical PBRTQC method. Furthermore, the authors developed a fusion model combining three ML algorithms (RF, SVM, and DNN) as a real-time quality control tool, assessed its performance on a dataset of clinical tPSA test results, and compared it with the traditional PBRTQC MovSD method [30].

Post-analytical Phase. In the post-analytical phase, AI enhances the reporting process by enabling automated validation and interpretation of results, thereby improving efficiency and reducing errors. By integrating automated verification, AI helps ensure that only confirmed and accurate results are reported into laboratory information systems (LIS) and electronic health records (EHR) [8].

In this stage of laboratory operations, AI has been applied to result verification, quality assurance, and the analysis of laboratory test outputs [9]. Validation of test results in the post-analytical phase represents the final critical step in quality assurance before issuing laboratory reports. ML models capable of learning from experience have gained interest for their potential in autoverification of test results. Demirci et al. (2016) [31] developed an artificial neural network (ANN)-based model for the automated verification of biochemical test results and confirmed its effectiveness across two test datasets.

To fully leverage the value of laboratory test data, numerous authors have investigated the application of various ML models for the analysis of laboratory test results. Several studies have demonstrated that ML models yield promising outcomes in predicting specific diseases, such as diabetes and its complications [32], liver diseases [33], hematological disorders [34], and the likelihood of acute kidney injury in hospitalized patients [35]. Yue et al. (2022) [36], using laboratory test results, demographic information, and other clinical data, developed ML models to predict whether septic patients would develop acute kidney injury. The use of ML models for sepsis prediction has, in recent years, emerged as an increasingly relevant area of research. However, most of these studies remain limited to patients in intensive care units (ICU) [37].

Examples of Artificial Intelligence Applications in Chemical/Biochemical Laboratories

Artificial intelligence can be applied in various areas of biochemical laboratory practice, serving multiple purposes. In the literature, the most frequently cited examples include AI applications for the automated interpretation of biomarker samples for disease diagnosis and monitoring, workflow optimization within the laboratory, and decision support [18, 26, 38, 39]. AI models, particularly neural networks, through the analysis of large biomarker datasets, can identify relationships and correlations that enable early disease detection (e.g., diabetes, cancer, and others), in some cases even prior to the manifestation of clinical symptoms [40]. By introducing automation in sample processing, data entry, and result analysis, AI contributes to the optimization of workflows in biochemical laboratories. On the one hand, automation reduces the need for human intervention, minimizes errors, improves laboratory throughput, and enhances quality control by enabling long-term data analysis, while also facilitating the timely prediction of errors or equipment failures [8, 41].

With the use of AI, laboratories can evaluate biomarker trends and thereby predict disease recurrence in patients. By analyzing metabolic profiles, the implementation of AI in biochemical laboratories can assist physicians in making decisions regarding personalized treatments. An AI-driven approach facilitates the development of patient-specific treatment plans. In other words, AI integrates patient data with biochemical parameters, providing clinicians with practical insights that support clinical decision-making [8].

Both research and diagnostic biochemical laboratories generate vast volumes of data. Traditional data analysis methods are often time-consuming and prone to human error, limiting the ability to reach rapid and reliable conclusions. AI addresses these challenges by automating complex analytical processes and uncovering patterns that might otherwise remain undetected by human analysis. In diagnostic laboratories, AI enhances the accuracy and speed of disease detection by analyzing complex biomolecular data (e.g., protein structures, genetic variations, and metabolite concentrations). AI-based models can predict disease states earlier than conventional diagnostic methods, enabling timely interventions and improving patient outcomes [8].

Dustin et al. (2022) [20] provided a tabular overview of selected examples of AI applications in chemical/biochemical laboratories.

Table 1. Selected examples of AI applications in medical chemical/biochemical laboratories (Adapted from [20])

Domain	Input Data (Features)	Output Data (Label)	Model	Use Case
PRE-ANALYTICAL PHASE				
Detection of wrong blood in tube (WBIT) [42]	Routine laboratory tests including electrolytes, urea, creatinine	Presence or absence of WBIT	Neural network	Identification of WBIT cases
Sample quality [43]	Coagulation test results	Presence or absence of clot in the sample	Neural network	Detection of clotted samples
ANALYTICAL PHASE				
Prediction/imputation of results [44]	Laboratory test data including vital signs, age, sex, and admission diagnosis	Normal or abnormal result	Ensemble (fuzzy model, logistic regression, random forest, gradient boosting trees)	Estimation of pre-test probability of laboratory examination
Diagnosis and risk prediction [45]	Laboratory test results including complete blood count and comprehensive chemistry panel	Objective remission, mismatch, or ranking	Ensemble (random forest)	Monitoring thiopurine therapy
Interpretation support (electrophoresis) [26]	Serum protein electrophoresis densitogram	Classification of interpretation	Deep neural network	Providing possible interpretations based on data
POST-ANALYTICAL PHASE				
Automated verification [31]	13 test results, 7 delta values, age, HIL index	Auto-reporting or withholding	Artificial neural network	Determination of whether a clinical result can be released

Challenges of Applying Artificial Intelligence in Medical Laboratories – Possible Solutions and Their Implementation

The application of AI in medical laboratories holds strong potential, but currently, only a small number of AI tools are used in diagnostic laboratories, and even fewer in clinical laboratories, as none of the available tools can fully meet all clinical needs. In any case, there is significant room for further research into AI tools [46].

According to Hou et al. (2024) [9], developers of AI models face issues related to data heterogeneity, lack of validation of developed AI models, interpretability of AI models, and insufficient involvement of laboratory staff in the AI model development process. A major barrier to the development and practical implementation of AI is the attitude people have towards this technology. Many studies have shown that laboratory staff lack adequate knowledge of AI and are preoccupied with the idea that AI models might replace them in the near future. This creates significant resistance during the process of implementing new technologies [47]. The initial investment costs for implementing AI in medical laboratories are high, and in many cases, the laboratory infrastructure is not adequate to support AI applications. Implementation of AI models in laboratories is also limited by serious issues related to data privacy and security [48]. Machines learn from limited and inadequate datasets and may make decisions that do not apply to a specific patient or could even endanger the patient's life.

To address the above-mentioned challenges, several issues need to be resolved in the future. The heterogeneity of data encountered by laboratories when applying AI models (i.e., models developed in one location being applied in another) requires the standardization and structuring of laboratory test data. Problems related to inadequate model validation call for extensive external validation to demonstrate the robustness and generalizability of the developed models. Issues arising from the interpretability of AI models (such as legal disputes, negligence by medical staff, etc.) require greater model transparency, which will clearly be a major challenge for future research. Laboratory personnel do not have access to the source code that defines the underlying algorithm framework. Laboratory test data is usually processed by IT professionals, not the laboratory staff, who only have access to the final product of the AI model. These practices in the development and application of AI models are likely to lead to corporate monopolies and misinterpretation of test results, ultimately affecting the quality of medical laboratory services. This problem can be addressed through the establishment of effective collaboration and open-source code sharing [9].

Existing guidelines for the development and regulation of AI model use in clinical laboratories must be further implemented and improved. The widespread adoption of AI technologies requires a readiness to change existing laboratory and clinical structures and attitudes toward this new technology. Therefore, there is a need to educate various stakeholders about AI technology and its use [49]. It is extremely important that, in the future, AI models most suitable for patients are selected, and accordingly, guidelines should be developed for the proper selection of methods for using AI systems in diagnostics [48]. Finally, future research should focus on validating AI models in clinical settings and maximizing their generalizability [9].

Ethical Issues Related to the Application of AI in Medical Laboratories

The use of AI in biochemical laboratories offers significant potential but also poses serious risks. To avoid potential dangers, a careful approach to development is required, along with adherence to ethical principles that emphasize the importance of fairness, transparency, and accountability in the use of artificial intelligence in laboratories. In addition, ethical frameworks highlight the need for data privacy, unbiased algorithms, and fair treatment of patients [8].

Insight into the Future Potential of AI Applications

Medical laboratories and diagnostic testing play a crucial role in healthcare by enabling earlier, faster, and more accurate diagnoses, which improve patient outcomes and can save lives. Advances in diagnostic technologies are further enhancing this field.

AI shows great potential for application in all phases of the laboratory testing process. With the continuous development of high-throughput technologies, omics data are rapidly accumulating, and extracting necessary information from vast amounts of omics data presents a daunting challenge. Some studies have been conducted on the integration and analysis of multi-omics data using AI models, which are capable of discovering new biomarkers [9, 50].

Effective integration of AI and ML into medical laboratories requires significant time and investment in resources. Interpreting AI recommendations is often challenging, but this investment can substantially improve laboratory performance. A practical approach involves identifying workflow obstacles within the laboratory and exploring purpose-built AI solutions that align with the lab’s specific needs [8].

It is expected that future laboratories will become increasingly automated, with greater use of robotics, AI, and the Internet of Things (IoT). However, widespread adoption of AI in clinical laboratories requires careful consideration of legal liability. Current uncertainties, lack of clarity, and misunderstandings surrounding sensitive personal data, data processing, consent, transparency, and data archiving raise complex legal questions about liability for decisions based on AI-driven diagnoses [51].

In the future, wearable sensors are also expected to become a major market for AI applications. As wearable sensors continue to evolve, they will collect large volumes of personalized data, and analyzing this data will make it easier to detect and predict several diseases that have traditionally relied on laboratory testing [52]. In recent years, several studies have explored the application of ML algorithms to wearable sensors for disease screening [53].

Conclusion

Artificial intelligence is redefining operations in medical laboratories, including chemical/biochemical labs. The application of AI enables automation, improved diagnostics, predictive analytics, and personalized patient care. AI applications will further enhance diagnostic accuracy and laboratory efficiency.

As AI continues to evolve, medical laboratories face the imperative to embrace integration responsibly, ensuring adherence to ethical principles and maintaining a strong focus on patient-centered outcomes. As AI continues to shape this field, its ethical use is crucial for ensuring fair, high-quality healthcare outcomes.

There is still a long way to go before a larger number of AI models are implemented in medical laboratories. Deeper, more comprehensive, and multicenter studies are needed. Future research should address current limitations in order to maximize the impact of AI through innovative applications in medical and research-based chemical/biochemical laboratories. This will require joint efforts from laboratory professionals, IT experts, and other stakeholders.

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VJEŠTAČKA INTELIGENCIJA U BIOHEMIJSKOJ LABORATORIJI - UTICAJ NA DIJAGNOSTIKU

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Sažetak. *Primjenjena vještačke inteligencije (AI) u medicinskim laboratorijama uticala je na promjenu u radu dijagnostičkih laboratorija. AI vodi ka optimizaciji radnog toka i utiče na operativnu efikasnost laboratorije. U ovom pregledu dat je prikaz najnovih istraživanja u oblasti primjene AI u biohemijskim laboratorijama. Izvršen je pregled recenziranih radova referisanih u više baza (Science Direct, PubMed, Scopus, Research Gate i Google Scholar) koji su objavljeni između 2020. i 2025. Pretraživanje je izvršeno na osnovu ključnih riječi koje povezuju AI i dijagnostičke laboratorije. Ovaj rad počinje sa kratkim pregledom AI i modelima AI koji se trenutno koriste u medicinsko-zdravstvenim laboratorijama. Nakon toga, objašnjeni su postojeći izazovi AI modela, moguća rješenja i njihova primjena, a na kraju dat je uvid u mogućnosti primjene AI u budućnosti. Posljednjih godina učinjeni su značajni pomaci u razvoju AI aplikacija u biohemijskim i kliničko-hemijskim laboratorijama. Očekuje se ubrzanje ovog trenda u narednim godinama. AI značajno poboljšava mnoge procese u laboratoriji. Postojeće aplikacije se odnose na automatizaciju toka rada, analizu podataka o biomarkerima, obradu rezultata u realnom vremenu, lakše donošenje odluka od strane kliničkog osoblja, itd. Međutim, postoje i pitanja koja zahtijevaju oprez tokom uključivanja AI u laboratorijsku praksu. Ona se odnose na brigu za integritet podataka, potencijalne predrasude o korištenim algoritmima i određena etička pitanja.Laboratorije su spremne za veću automatizaciju i inkorporaciju AI i IoT tehnologija u budućnosti. Postojeće aplikacije utiču na provođenje svih faza analize u hemijskim i biohemijskim dijagnostičkim laboratorijama. Iako primjena AI u laboratorijskoj dijagnostici predstavlja potencijal za poboljšanje tačnosti rezultata i efikasnosti rada, te unapređenje ishoda zdravstvene zaštite, neophodno je odgovoriti na neka etička pitanja i izmijeniti pravni okvir za rješavanje pitanja vezanih za privatnost podataka i odgovornost algoritama.*

Ključne riječi*: Vještačka inteligencija, AI, Biohemijska laboratorija, Dijagnostička laboratorija*