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Deep Learning for Rapid Detection of Bacterial Infections from Microscopic and Clinical Data: AI-Based Identification of *Staphylococcus aureus*

Fatemeh Mousalou [1]*, Seyedeh Negin Nedaei [2]

[1]Department of Microbiology, Ard.C., Islamic Azad University, Ardabil, Iran
[2]Department of Microbiology, Ard.C., Islamic Azad University, Ardabil, Iran

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Abstract

Infections of the bloodstream, pneumonia, and bone and joint infections are all well-known symptoms of *Staphylococcus aureus*, which are frequently fatal. MRSA, a potentially harmful strain that is resistant to methicillin, an antibiotic produced from penicillin, is associated with AMR. It is still quite challenging to diagnose and treat bacterial infections in the medical industry in the modern world. Artificial Intelligence (AI) has emerged as a potent new method for detecting and treating bacterial infections. Since timely diagnosis and treatment can improve morbidity and mortality for bacterial diseases and other infectious diseases, such hepatocellular carcinoma brought about by hepatitis B and C, or non-infectious disorders such acute necrotizing pancreatitis. Because of its prevalence and considerable clinical load in hospitals, methicillin-resistant *Staphylococcus aureus* (MRSA) bloodstream infection (BSI) is a major worry. Due to its resistance to several antibiotics and associated complications like septic shock and metastatic infections, it poses a serious clinical challenge. For categorizing bacterial antibiotic resistance and susceptibility, deep learning is preferred over traditional machine learning due to its better performance. The macroscopic level at which traditional techniques, like the Kirby-Bauer disk-diffusion test, are performed, restricts accuracy and ignores important microscopic bacterial interactions. There are still many obstacles to overcome despite the tremendous promise of AI to revolutionize tailored treatment. Ultimately, as AI technology develops and is used more extensively, it will help doctors to treat bacterial infections more effectively, advancing the medical industry toward more accurate, efficient, and individualized treatment.

Key words: *Staphylococcus aureus*, MRSA, Bloodstream infection, Artificial intelligence, Bacterial Infection, Deep learning.

*Corresponding Author: E-mail: fatemehmousalou812@gmail.com

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Graphical Abstract

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Introdoction

Gram-positive, cocci-shaped *Staphylococcus aureus* bacteria proliferate in the distinctive grape clusters(Sanchini, 2022), It was first isolated from the British surgical wound infection Alexander Ogston, a surgeon, in 1882 (Sinoliya et al., 2023) , acts as an opportunistic pathogen and a zoonotic pathogen, capable of causing various diseases in humans(Zhang et al., 2022). Staphylococci, as a cause of infections acquired in hospitals, raise the risk of developing illnesses like wound infections, sepsis, and skin infections in individuals(Leili et al., 2024). S. aureus possesses a remarkable capacity to quickly develop resistance. Environmental factors, along with damage to cell membranes or DNA, can affect the rapid emergence of antibiotic resistance(Rasmi et al., 2022). The Grampositive bacterium known as methicillin-resistant *Staphylococcus aureus* (MRSA) was treated with a number of beta-lactam antibiotics, including penicillin, oxacillin, and methicillin. However, because of a change in the genetic makeup of the original strain, *Staphylococcus aureus* has become resistant to all of these (Sinoliya et al., 2023). Antibiotic resistance (AR) is a naturally happening event primarily made up of acquired adaptive mechanisms. These systems help bacteria to withstand and endure the threats posed by antibiotics(Popa et al., 2022). Bacterial strains that are resistant to antibiotics pose a significant danger to human health. As antibiotic resistance in common human germs rises, there are fewer antibiotics that still work against infections. The swift rise in antibiotic resistance has surpassed the progress in creating new antibiotic drugs, posing a risk of concluding the golden era of antibiotics and ushering in the post-antibiotic period(Nikolic & Mudgil, 2023). To overcome AR, global initiatives should be developed and implemented across nations. Such programs are presently being created with the assistance of computer systems built on deep learning(Popa et al., 2022). In recent years, machine learning and deep learning have gradually emerged as new methodologies. The ideas, uses, or fields of application of machine learning and deep learning have been discussed by numerous academics (Shao et al., 2024). In clinical practice, machine learning (ML) offers the possibility of becoming a paradigm-changing decision-support instrument. treatment, diagnosis at present, clinical criteria are used to determine prognosis and treatment. This clinical practice pattern, known as the "knowledge driving decision," is equivalent to the individual experience of doctors. but real patient circumstances are often more complex than a single guideline or individual. the doctor's expectations. One of the greatest dangers is antibiotic resistance (AMR). issues in the area of infectious diseases. It was predicted that in 2019, 1.27 million people would die from bacterial AMR. When a patient is suspected of having a resistant bacterial infection, physicians always choose antibiotics empirically rather than relying on the drug susceptibility results. It also planned to compare the predictive performance between the ML algorithm and the risk score system in this study (Tang et al., 2022). The rate and effectiveness with which pathogens conduct a sequence of biochemical reactions during their life processes is referred to as their metabolic activity. Culture-based agar plate counting is the most conventional method for detecting pathogen activity because it depends on the pathogen's capacity for growth. This approach involves analyzing bacterial morphology under a microscope and looking for colony development on plates to determine pathogen activity (Liu et al., 2025). To overcome these shortcomings, novel micro- and nanotechnology techniques for bacterial identification and AST are being developed. Among these are molecular approaches like mass spectrometry, nanoparticles, synthetic biology, hybridization probes, multiplex PCR, and phenotypic methods like microfluidic bacterial cultures (Ardila et al., 2025). Some studies have used these algorithms and models to predict HAIs based on risk factors and to enhance patients' health results. The purpose of this scoping review is to identify the features of AI applications used in the management of bacterial illnesses (Abu-El-Ruz et al., 2025).

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From *Staphylococcus aureus* to Bloodstream and Urinary Infections: Clinical Importance and Diagnostic Limitations

Infections caused by *S. aureus* are a significant threat to public health (Bashabsheh et al., 2024) ,One of the leading opportunistic bacterial pathogens of the human population, s is a common colonizer of it. human beings, which are responsible for significant morbidity and mortality worldwide (Howden et al., 2023) . The bacteria establishes itself in thethe mucous membranes and skin of the front nostrils, the perineum, the urogenital system, and the digestive tract among other places, the pharynx and the tract. The virulence factors produced by Effective therapy depends on Staphylococcus aureus. human and animal illness (Pal et al., 2021). In each of its hosts, S. aureus causes a wide range of symptoms. The interactions between *S. aureus* and its host are influenced by a number of intricate variables, such as the host's health, the genetic makeup of the *S. aureus* strain, and the location of the host's colonization (Park & Ronholm, 2021). Due to the rise in healthcare procedures and the usage of indwelling devices, the incidence of the disease burden caused by *Staphylococcus aureus*, a major cause of bloodstream infections, has increased over the past several decades (Grillo et al., 2022) . The frequency of *S. aureus* bacteremia (SAB) is influenced by the risk factors of the studied population as well as the healthcare system's infection control procedures. Monitoring the incidence of SAB trends is essential in determining its effects on public health organizations and infrastructure. to improve the creation of methods for infection prevention and control (Hindy et al., 2022). Gram-positive bacteremia is more prevalent than gram-negative bacteremia, which is categorized into gram-positive and gram-negative bacteremia. This might be explained by the increased use of intravenous catheters, prosthetic implants, invasive procedures, and the widespread use of fluoroquinolones for antibiotic prophylaxis, all of which increase the risk of gram-positive growth.

In gram-positive bacteremia, there are certain typical associations between species and locations of localized infections, such as between pneumococci and pneumonia, while S. aureus infection sites are frequently more hidden and, as a result, are more frequently discovered as the cause of BSI of unknown origin (Hess, 2023). Intermittent bacterial presence in the blood is a characteristic of Gram-negative bacteremia, which frequently originates as a secondary infection that spreads from an initial source to the bloodstream. Underlying 26.6% of instances, *E. coli* is the most prevalent species found in community-onset bacteremia and the second most prevalent in hospital-onset bacteremia. *A. baumannii*, which accounts for 3.2% of cases of hospital-onset bacteremia, is a frequent cause of the condition, but it is not very common in community-onset infections. The third most common species responsible for 7.2% and 8.8% of cases of community- and hospital-onset bacteremia, respectively, is *K. pneumoniae. P. aeruginosa* is the fourth most common species isolated from hospital-onset bacteremia (7.4% of cases) and ranked fifth among species causing community-onset bacteremia (7.3% of cases) (Holmes et al., 2021). The most frequent cause of infections caused by multidrug-resistant bacteria in the United States is methicillin-resistant *Staphylococcus aureus* (MRSA). Historically, MRSA bacteremia has been linked to higher death rates than its more susceptible relative (Parsons et al., 2023) . A fever alone might be the symptom of *Staphylococcus aureus* bacteremia. prompting diagnostic blood cultures(Figure1). In contrast, patients may have symptoms originating from a source such as a skin and soft tissue infection or a site of metastatic infection (e.g., back pain from vertebral osteomyelitis). About 73% of individuals with *S aureus* fever occurs in 42% of bacteremia cases, chills in 18%, and changes in mental status in 18% (Tong et al., 2025). One of the most prevalent infectious illnesses in people, whether in a community or clinical

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environment, is urinary tract infection (UTI) (Yousefi et al., 2016) . Urinary tract infections (UTIs) caused by *Staphylococcus aureus* are uncommon (0.5%–1%). Finding *S. aureus* in urine samples might indicate asymptomatic colonization or point to *S. aureus* bacteremia (SAB), which is brought about by hematogenous seeding (Schuler et al., 2021) . Despite the fact that S. aureus is antibiotic treatment accounts for 0.5 to 6% of UTI cases. The likelihood of a symptomatic UTI related to this species is high. It should be taken into consideration and is advised. The emergence of may result from antibiotic treatment. *S. aureus* that is multidrug-resistant (MDR), which would cause restrictions in the selection of therapeutic alternatives (Goudarzi et al., 2019) . Pyelonephritis, which is when the infection has spread to the kidneys and necessitates prompt medical care, is frequently indicated by fever during a urinary tract infection (UTI). Kidney UTIs can be fatal if they cause septicemia, which causes an infection in the bloodstream, and can result in systemic infection. Women are more susceptible to UTIs than men. Several factors contribute to this, including a shorter urinary tract, the urethral opening's proximity to the anal aperture, hormonal imbalances and changes that cause the urethral pH to increase, and the use of contraception and spermicide (Balamurugan et al., 2015) . pyelonephritis with emphysema found in 90% of diabetic patients, is a rare inflammatory disorder of the kidneys brought on by untreated diabetic urinary tract infections, which cause gas production in the parenchyma environment and persistent necrosis of bacterial origin. Pyelitis of emphysema, This condition is marked by significant tissue necrosis in the kidney's parenchymal regions and is more lethal in women than in males. Cystitis with emphysema A particular kind of urinary tract infection that is made worse by an overproduction of air and air sacs getting stuck in the bladder wall and tube. Neurogenic bladder, blockage, or catheterization are predisposing factors. According to demographic data, women are more prone to the illness than males (Kaur et al., 2022) . A septic embolism to the kidney and subsequent identification in the urine were signs of an invasive illness brought on by *S. pyogenes* in an immunocompetent kid. These instances demonstrate that certain bacteria are able to be identified in urine during systemic infections. Because the transfer from blood to urine seems to occur more frequently in S. aureus than in other pathogens, *S. aureus* could be utilized as a model organism to investigate the pathogenesis's principles in order to overcome the barriers between the blood and urine in vivo (Schuler et al., 2021). We look at what we know the function of biofilms, immunometabolism, and trained innate *S. aureus* avoidance mechanisms in the immune evasion molecules of *S. aureus* immunity. We also look at how well *S. aureus* adapts to and targets its hosts. and provide a summary of our current understanding of the interaction between colonizing A summary of our developing understanding of *S. aureus* genomic flexibility, antibiotic resistance, and persistence, together with other bacteria (Howden et al., 2023).

Deep learning

Machine learning and deep learning have quickly become effective tools in various areas, such as image and speech recognition, natural language processing, and medicine(Sharifani & Amini, 2023). Using artificial neural network (ANN) architecture to learn from massive datasets and carry out sophisticated operations, deep learning is a subset of machine learning. The capacity of deep learning methods to replicate the intricate information processing capabilities of the human brain is one of their primary benefits. This is due to the increased processing power of microprocessors, better algorithm creation, and access to vast datasets for model training. An ANN is made up of interconnected nodes (often called processing elements or neurons) that can extend across several layers, depending on the complexity of the jobs and the capacity of the available hardware.

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A deep learning model gathers more complex and detailed insights as the number of its structural layers grows, leading to improved effectiveness with extensive datasets and training cycles. This process guarantees accurate identification of patterns within the data(Shobayo & Saatchi, 2025).

Deep learning: CNN and RNN

Convolutional Neural Networks (CNNs) represent a strong category of deep learning models that are extensively utilized in numerous tasks, such as object detection, speech recognition, computer vision, image classification, and bioinformatics(Shiri et al., 2023). CNNs consist of four primary elements: (a) trainable convolutional filter banks, (b) nonlinear activation functions, (c) reduction of spatial dimensions (achieved through pooling or strided convolution), and (d) a prediction module, typically made up of fully connected layers that function based on a comprehensive representation of the instance(Choudhary et al., 2022). CNN uses a system with two parts that works together as a classifier and a feature extractor. This setup allows it to automatically find important features and train from start to finish with very little need for preparing the data beforehand(Shiri et al., 2023). Recurrent Neural Networks, or RNNs, are a type of advanced learning model that have a built-in memory, which allows them to understand sequences. Unlike regular neural networks that view inputs as separate items, RNNs take into account the order of inputs over time, making them ideal for jobs that require understanding sequences of information. By using a loop, RNNs perform the same action on each part of a sequence, where the calculation at the moment relies on both the current input and the previous calculations(Shiri et al., 2023).

Deep Learning Applications in Microscopic Image Analysis

Deep neural networks represent the latest advances in many computer vision challenges and frequently surpass traditional image analysis methods. In the past few years, deep learning has gradually transitioned from the realm of computer science into microscopy applications, showing remarkable success in fields like cancer detection, super-resolution, noise reduction, and stain-free imaging(Körber, 2023). Deep learning is an advanced technology that has quickly emerged as the preferred approach for analyzing medical images (Habibur et al., 2024). Its speedy and strong capabilities in identifying, separating, monitoring, and categorizing abnormal anatomical features can assist healthcare professionals in their everyday clinical activities. As a result, applications using deep learning for diagnosing illnesses will enhance doctors' abilities and facilitate quicker decision-making in healthcare settings(Tsuneki, 2022).

Segmentation and classification techniques for blood and urine sample images

The analysis of crystals found in urine sediment, which are the solid parts of urine, helps in screening tests and is a standard part of medical check-ups. Urinary sediment crystals are generally examined by looking at them through a microscope. While there are machines that can help with this process, manual sorting is still necessary, which takes a lot of time and can differ based on the person doing the test and the laboratory used(Nagai et al., 2022). Devices that automatically analyze urine sediment are essential for identifying urinary tract infections, as they provide immediate analysis of data and speed up the process of diagnosing patients(Akhtar et al., 2024).

Deep Learning for Clinical Data Analysis

Today, the amount and diversity of information that may be used to analyze and forecast clinical results are outside the capacity of any one person to grasp (Pettit et al., 2021).

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Using a single modality to arrive at a diagnosis or prognosis with deep learning approaches has been highly successful in several studies. Nonetheless, because different clinical modalities may have different data formats and hold different information (complementary information of a subject), effectively merging multimodal data is not an easy undertaking in method design (Cui et al., 2023). Although successful in many instances, traditional medical diagnostics have depended on unimodal data sources, such radiological images, clinical notes, or physiological signals that are analyzed separately (Abu-El-Ruz et al., 2025). However, these unimodal systems do not completely reflect the complexity of human diseases, which are frequently characterized by varied and interconnected signals (Jandoubi & Akhloufi, 2025). Using the power of information technology, AI-driven healthcare is becoming a revolutionary force in the healthcare environment and aims to transform clinical practices (Xu et al., 2024). A wide range of sources, such as medical imaging (like magnetic resonance imaging [MRI], computed tomography [CT] scans, and x-rays), lab test findings, electronic health records (EHRs), wearable devices, and environmental sensors, produce enormous amounts of data in the healthcare industry (Hao et al., 2025). The majority of modern uses of artificial intelligence (AI) in medical diagnosis are limited to data from a single modality. Using clinical records, radiology, CT scans, MRI, and other methods, researchers have conducted in-depth studies on the early identification of a variety of medical ailments in individuals (Kumar et al., 2024). Within the radiological medical ecology, AI has the potential to be a powerful support tool. However, the use of AI raises ethical issues3 and security concerns4, such as data breaches, automated medical choices, skewed data, and clinical consequences (Simon et al., 2025). Medical image analysis, an essential aspect of contemporary healthcare, depends significantly on cutting-edge technology. Computational methods for retrieving useful data from images. Deep learning, Recurrent neural networks (RNNs) and CNNs, in particular, have become a potent instrument in this field. offering unparalleled capacity for automated feature extraction, pattern identification, and decision By dealing with the aforementioned high dimensionality and temporality of medical data, deep learning (DL) methods have demonstrated exceptional performance in a variety of healthcare prediction applications. These improved neural network approaches are able to learn valuable representations of key factors, such as esoteric medical concepts and their interactions, from high-dimensional raw or minimally processed healthcare data (Morid et al., 2023) in isolated locations AI tools may function as complete replacements in the absence of specialist availability. independent preliminary readings, akin to telemedicine services (Rao et al., 2025). By integrating multimodal data into prediction and classification models to mimic integrative human clinical decision-making, AI systems may gain a lot. This can lead to the discovery of novel biomarkers and treatment targets, enhance model performance, and increase their robustness and accuracy (Pahud de Mortanges et al., 2024).

In specific groups, such as babies and the elderly, where pain is difficult to measure, the characteristics of AI systems may be used to determine pain intensity and direct therapy(Liang et al., 2025). Infants are unable to express their discomfort verbally, which frequently results in underdiagnosis and subpar therapy. This improper pain management in infants is associated with behavioral difficulties, increased attentiveness, and possible structural changes to the brain that affect learning and development. AI approaches evaluate behavioral responses (Cascella et al., 2024) like facial (Yan et al., 2023), sobbing sounds, and body motions expressions in order to overcome these challenges. AI technologies evaluate physiological signs and nonverbal cues to offer unbiased pain assessments for cognitively impaired elderly people (Cascella et al., 2024). Unimodal research often makes use of pathology images and related clinical data, such as cancer kinds or grading. Simple and unambiguous aim is ideal for unimodal research utilizing AI-based models in clinical applications and translations (Qiao et al., 2022).

Furthermore, in addition to recurrent neural networks (RNN), which can use and analyze numerical data (clinical parameters and biological indicators) and textual data taken from EHRs, multi-task deep learning neural networks such as UNet and MTNet were employed to integrate various data modalities (Siam et al., 2023).
There is a lot of potential for integrating deep learning algorithms into radiological workflows to improve increasing the accuracy of diagnosis and improving patient care (An et al., 2023). In several studies, models that use a combination of transformers, convolutional networks, and hybrid attention mechanisms have demonstrated excellent performance in disease categorization, segmentation, retrieval, and risk prediction (Jandoubi & Akhloufi, 2025). For a more precise clinical diagnosis and prognosis, medical experts usually compare and link the data (Shetty et al., 2022). To gather and synthesize the available literature in order to create a basis for future study, medical healthcare information is combined using various fusion methodologies to create multimodal data (Teoh et al., 2024). To sum up, multimodal AI is a major improvement in precision medicine because it combines different modalities to provide individualized therapies and improve patient care (Isavand et al., 2024) . As part of a service for anomaly detection, predictive analysis, and ensemble modeling, AI requires quick, flexible hardware and software as well as data-mixing capabilities (Laghari et al., 2024). We put a special emphasis on significant AI techniques for integrating prevalent data modalities and discuss their possible uses in clinically relevant domains (Zhang et al., 2025).

Conclusion

Bacterial infections create a major safety issue, so prompt and precise diagnosis is crucial for effective treatment and outcomes. Conventional diagnostic techniques, although dependable, tend to be sluggish and do not fulfill immediate clinical requirements. On the other hand, new technologies provide improved efficiency but are frequently expensive and hard to access The use of artificial intelligence in managing infections should be enhanced in poorer nations. There should be increased investment in proven models for infection control to ensure they are used effectively and to address existing issues. Although artificial intelligence holds great promise for transforming individualized healthcare, there are still numerous obstacles to address. These include concerns regarding data security, the unclear processes behind Al decision-making, and the slow advancement in translating research findings into real-world uses. It is essential to tackle these issues through collaboration, creativity, and thorough policy formation to fully leverage Al's capabilities in improving personalized medical care and treatment results

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