Narrative Review

Predictive Modelling of Clinical Deterioration Using Sequential Laboratory Trends with Machine Learning Techniques

Clinical Deterioration Using Sequential Laboratory Trends

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ABSTRACT

Objective: To summarize the role of sequential laboratory trends and machine learning techniques in predicting clinical deterioration among hospitalized patients.

Place and Duration of Study: This study was conducted as a narrative review article from June 2024 to April 2025.

Methods: Relevant literature was searched through PubMed, Google Scholar, Scopus, Web of Science, and IEEE Xplore which was published till April 2025. Evidence regarding the predictive value of serial laboratory measurements and the performance of various machine learning algorithms was synthesized.

Results: Sequential changes in laboratory parameters, including serum creatinine, lactate, white blood cell count, platelet count, electrolytes, inflammatory markers, and arterial blood gases, were identified as important early indicators of worsening organ dysfunction and impending clinical deterioration. Machine learning approaches, such as logistic regression, random forest, gradient boosting, support vector machines, artificial neural networks, and recurrent neural networks, demonstrated the ability to identify complex temporal patterns and improve prediction accuracy compared with conventional risk assessment methods.

Conclusion: Predictive modelling based on sequential laboratory trends and machine learning techniques represents a promising strategy for the early detection of clinical deterioration in hospitalized patients. Further research focusing on robust validation, interpretability, and seamless clinical integration is required to optimize patient outcomes and enhance healthcare safety.

Key Words: Clinical deterioration; Machine learning; Sequential laboratory trends; Electronic health records; Early warning systems; Risk stratification.

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INTRODUCTION

Clinical deterioration in hospitalized patients remains a major challenge in modern healthcare, often leading to increased morbidity, prolonged hospital stays, and higher mortality rates. Early identification of patients at risk of deterioration is critical for timely intervention and improved clinical outcomes[1].

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Traditional methods of monitoring, including periodic vital sign assessments and clinician judgment, are often limited by subjectivity and may fail to detect subtle physiological changes that precede acute events. As a result, there is growing interest in leveraging data-driven approaches to enhance early detection and risk stratification in clinical settings[2]. Laboratory investigations are routinely performed in hospitalized patients and provide objective, quantifiable insights into physiological and biochemical status. Importantly, changes in laboratory parameters over time rather than isolated values may better reflect evolving pathophysiological processes[3]. Sequential laboratory trends, such as rising inflammatory markers, worsening renal function, electrolyte imbalances, or declining hematological indices, can serve as early indicators of clinical deterioration. However, the complexity and volume of such longitudinal data make it difficult for clinicians to interpret patterns accurately in real time, particularly in high-acuity environments. Recent advances in machine learning have opened new avenues for analyzing large and complex healthcare datasets[4]. Machine learning algorithms can identify nonlinear relationships, temporal patterns, and interactions among multiple variables that may not be apparent through conventional statistical methods. By integrating sequential laboratory data into predictive models, these techniques can generate dynamic risk scores and provide early warnings for clinical deterioration[5]. Models such as random forests, gradient boosting machines, support vector machines, and deep learning architectures including recurrent neural networks and long short-term memory networks have shown considerable promise in capturing temporal dependencies and improving predictive accuracy in various clinical contexts[6]. The application of machine learning in predictive modelling has demonstrated encouraging results in areas such as sepsis detection, intensive care monitoring, and hospital readmission prediction[7-9]. However, many existing models rely heavily on vital signs or static baseline variables, with relatively limited focus on the prognostic value of sequential laboratory trends[10]. Furthermore, there is a need for models that are not only accurate but also interpretable and clinically actionable. Black-box models, although powerful, may face resistance in clinical adoption due to lack of transparency, highlighting the importance of explainable artificial intelligence in healthcare[11-13].

METHODS

Traditional methods of monitoring, including periodic vital sign assessments and clinician judgment, are often limited by subjectivity and may fail to detect subtle physiological changes that precede acute events. As a result, there is growing interest in leveraging data-driven approaches to enhance early detection and risk stratification in clinical settings[2]. Laboratory investigations are routinely performed in hospitalized patients and provide objective, quantifiable insights into physiological and biochemical status. Importantly, changes in laboratory parameters over time rather than isolated values may better reflect evolving pathophysiological processes[3]. Sequential laboratory trends, such as rising inflammatory markers, worsening renal function, electrolyte imbalances, or declining hematological indices, can serve as early indicators of clinical deterioration. However, the complexity and volume of such longitudinal data make it difficult for clinicians to interpret patterns accurately in real time, particularly in high-acuity environments. Recent advances in machine learning have opened new avenues for analyzing large and complex healthcare datasets[4]. Machine learning algorithms can identify nonlinear relationships, temporal patterns, and interactions among multiple variables that may not be apparent through conventional statistical methods. By integrating sequential laboratory data into predictive models, these techniques can generate dynamic risk scores and provide early warnings for clinical deterioration[5]. Models such as random forests, gradient boosting machines, support vector machines, and deep learning architectures including recurrent neural networks and long short-term memory networks have shown considerable promise in capturing temporal dependencies and improving predictive accuracy in various clinical contexts[6]. The application of machine learning in predictive modelling has demonstrated encouraging results in areas such as sepsis detection, intensive care monitoring, and hospital readmission prediction[7-9]. However, many existing models rely heavily on vital signs or static baseline variables, with relatively limited focus on the prognostic value of sequential laboratory trends[10]. Furthermore, there is a need for models that are not only accurate but also interpretable and clinically actionable. Black-box models, although powerful, may face resistance in clinical adoption due to lack of transparency, highlighting the importance of explainable artificial intelligence in healthcare[11-13].

Selection of Articles: Articles were selected if they discussed machine learning or artificial intelligence methods for predicting clinical deterioration in hospitalized patients. Studies using laboratory parameters, time-series clinical data, electronic health records, or sequential patient monitoring data were included. Preference was given to recent original articles, review articles, and clinically relevant prediction model studies. Case reports, editorials, letters to the editor, opinion-based articles, non-English articles, and studies not related to clinical deterioration or machine learning were excluded.

Data Extraction: Information was extracted regarding author, year of publication, study population, laboratory variables, machine learning algorithms, predicted clinical outcomes, model performance, and major findings. Attention was given to studies using sequential laboratory trends rather than single-point laboratory values. The extracted information was reviewed and summarized narratively. The findings were organized according to the role of laboratory trends, commonly used machine learning techniques, predicted outcomes, clinical usefulness, limitations, and future directions.

Clinical deterioration in hospitalized patients remains one of the most significant contributors to preventable morbidity and mortality in modern healthcare systems. It refers to a progressive decline in a patient’s physiological condition that may ultimately result in severe complications such as organ dysfunction, unplanned intensive care unit (ICU) admission, cardiac arrest, prolonged hospitalization, or death if not recognized and managed promptly[1]. Deterioration may occur suddenly or evolve gradually over hours to days, often preceded by subtle physiological, biochemical, or clinical warning signs that may be overlooked in busy clinical environments[14]. Hospitalized patients, particularly those admitted to medical wards, emergency units, and postoperative recovery settings, remain vulnerable to clinical decline due to underlying disease progression, infection, treatment-related complications, metabolic disturbances, or acute organ dysfunction[15]. Common causes include sepsis, respiratory failure, acute kidney injury, electrolyte imbalance, myocardial ischemia, hemorrhage, and neurological deterioration[4]. Timely identification of these changes is critical because delayed intervention significantly worsens outcomes and increases mortality risk. Despite this, failure-to-rescue remains a persistent problem due to delayed recognition, inadequate monitoring, fragmented communication, and variability in clinician response[16]. Traditional monitoring systems primarily depend on bedside clinical assessment and early warning scores such as the Modified Early Warning Score (MEWS), National Early Warning Score (NEWS), and Sequential Organ Failure Assessment (SOFA). These scoring tools are widely used to identify deteriorating patients by integrating vital signs such as respiratory rate, heart rate, blood pressure, oxygen saturation, and temperature[7].

Role of Sequential Laboratory Trends

Sequential laboratory trends play a critical role in the early identification of clinical deterioration among hospitalized patients. Unlike isolated laboratory measurements taken at a single time point, sequential laboratory monitoring provides dynamic information regarding the progression or improvement of a patient's physiological status over time[17]. Clinical deterioration is often not an abrupt event but rather a gradual biological process characterized by evolving biochemical abnormalities before overt symptoms become clinically apparent. Therefore, temporal laboratory changes may serve as early indicators of impending deterioration, allowing timely intervention and improved patient outcomes. Routine laboratory investigations are integral to inpatient care and provide objective insights into organ function, inflammatory status, metabolic balance, and systemic physiological stress. Commonly monitored parameters include complete blood count, serum electrolytes, renal function tests, liver enzymes, inflammatory markers, coagulation profiles, lactate, arterial blood gases, and cardiac biomarkers[18].

For example, a progressive rise in serum creatinine over successive measurements may suggest worsening renal function before overt acute kidney injury becomes clinically obvious[19]. Similarly, increasing serum lactate may reflect deteriorating tissue perfusion, occult shock, or developing sepsis even when vital signs remain temporarily stable[20]. Progressive leukocytosis or neutrophilia may signal worsening infection, while falling hemoglobin may suggest occult bleeding or marrow suppression. Temporal trends are particularly important because clinical physiology is dynamic rather than static. A laboratory value that remains within the conventional "normal" range may still be clinically concerning if it shows rapid deterioration relative to the patient's baseline[3]. For instance, creatinine rising from 0.7 to 1.2 mg/dL may remain technically within acceptable limits but could represent substantial renal decline. Static threshold-based systems may fail to detect such early warning patterns, whereas sequential analysis captures evolving trajectories. Laboratory trends are also less vulnerable to observer bias compared with subjective clinical assessments. Vital signs may be inaccurately recorded due to human error, inconsistent technique, or workload limitations, whereas laboratory results are generated using standardized analytical methods[4].

Machine Learning Techniques in Prediction Models

Machine learning (ML) has emerged as a transformative analytical approach in modern healthcare, particularly in predictive modelling for early detection of clinical deterioration. Unlike traditional statistical models that rely on predefined assumptions and linear relationships, machine learning algorithms can process large multidimensional datasets, recognize hidden patterns, model nonlinear interactions, and continuously improve predictive performance through iterative learning. These characteristics make machine learning especially valuable in hospital settings, where patient deterioration is influenced by complex interactions among physiological, biochemical, demographic, and treatment-related variables. Traditional clinical prediction systems such as MEWS, NEWS, and SOFA are useful bedside tools but remain limited by their dependence on manually selected variables, threshold-based scoring, and static interpretation[11].

Several machine learning techniques have been applied in healthcare deterioration prediction. Logistic regression, although traditionally considered a statistical method, remains one of the most commonly used baseline machine learning classifiers due to its simplicity, interpretability, and robust performance in binary outcome prediction[13]. In clinical deterioration modelling, logistic regression has been used to predict ICU transfer, mortality, and sepsis using combinations of laboratory values, demographics, and clinical observations. Decision trees are another commonly used machine learning approach. These models classify patients through hierarchical branching decisions based on predictor thresholds[14].

DISCUSSION

Predictive modelling of clinical deterioration has emerged as an increasingly important area in modern healthcare due to the growing need for early recognition of patient instability and prevention of adverse outcomes. Hospitalized patients frequently demonstrate physiological and biochemical warning signs before overt clinical collapse; however, conventional monitoring approaches often fail to recognize these subtle dynamic changes in time. This review highlights the evolving role of sequential laboratory trends combined with machine learning techniques in improving prediction of clinical deterioration, offering a more data-driven and proactive approach to inpatient care[21]. One of the major findings from the reviewed literature is that clinical deterioration is rarely a sudden isolated event but rather a progressive process characterized by evolving physiological and biochemical abnormalities. Traditional early warning systems such as NEWS, MEWS, and SOFA remain clinically useful, but their dependence on threshold-based scoring and intermittent bedside observations limits predictive sensitivity, especially in patients whose deterioration follows non-linear or atypical patterns[22]. Previous studies have shown that static scoring systems may miss early deterioration signals that are detectable through temporal data analysis. This limitation has created a need for more adaptive predictive strategies capable of recognizing hidden clinical trajectories[22-25].

Sequential laboratory trends represent an important advancement in this regard. Unlike isolated laboratory values, serial biochemical measurements provide dynamic insight into organ function, inflammatory progression, metabolic instability, and evolving systemic stress. Progressive changes in creatinine, lactate, platelet count, leukocyte count, electrolytes, arterial blood gases, and inflammatory biomarkers often precede overt clinical decline[26]. The reviewed literature consistently suggests that temporal laboratory monitoring offers superior predictive information compared with single-point measurements, particularly for identifying sepsis, acute kidney injury, respiratory failure, and impending ICU transfer. Another important observation from this review is the increasing effectiveness of machine learning in predictive healthcare applications[27]. Conventional statistical models often struggle to handle high-dimensional datasets, temporal dependencies, and nonlinear predictor interactions. Machine learning algorithms such as logistic regression, decision trees, random forests, gradient boosting, support vector machines, artificial neural networks, and recurrent neural networks demonstrate significant advantages in this context. These techniques can process large clinical datasets, detect complex hidden relationships, and continuously improve predictive performance[28].

CONCLUSION

Predictive modelling of clinical deterioration using sequential laboratory trends and machine learning techniques represents a promising advancement in modern healthcare. Unlike conventional monitoring systems that rely primarily on static observations and threshold-based scoring, these approaches enable dynamic assessment of patient risk by capturing evolving biochemical and physiological changes over time. Sequential laboratory trends provide valuable early indicators of organ dysfunction and systemic deterioration, while machine learning algorithms offer the capability to analyze complex multidimensional clinical data with greater accuracy and adaptability.

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