INDIAN SOCIETY OF HYPERTENSION

HYPERTENSION JOURNAL
www.hypertensionj.com

Review Article

Artificial Intelligence and Early Detection of Diabetic-Hypertensive Emergencies in the Emergency Room

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ABSTRACT

The global surge in diabetes mellitus and hypertension has led to an increased incidence of acute metabolic and cardiovascular emergencies. Early recognition and timely management of these emergencies—such as diabetic ketoacidosis (DKA), hyperosmolar hyperglycemic state (HHS), hypertensive crisis, and stroke—are critical to prevent morbidity and mortality. Artificial Intelligence (AI) has emerged as a transformative tool in healthcare, capable of integrating clinical, biochemical, and hemodynamic data for real-time risk prediction and decision support. This narrative review explores the evolving role of AI in the early detection and management of diabetic-hypertensive emergencies in the emergency room (ER), highlighting pathophysiological interlinks, current applications, challenges, and future directions.

Keywords: Artificial Intelligence, Diabetic ketoacidosis, Hypertension

DOI: 10.61081/htnj/25v11i304

INTRODUCTION

Diabetes mellitus and hypertension are two of the most prevalent chronic diseases worldwide, often coexisting and amplifying each other's complications. The interplay between hyperglycemia and elevated blood pressure predisposes patients to a spectrum of acute emergencies—ranging from hypertensive encephalopathy to diabetic ketoacidosis (DKA) and hyperglycemic crises with target organ damage including auto-amputations reporting to Emergency.[1]

Emergency physicians frequently face diagnostic challenges due to overlapping clinical presentations, time-sensitive management windows, and limited resources. Artificial Intelligence (AI) systems—particularly those based on machine learning (ML) and deep learning (DL)—offer unprecedented opportunities to enhance triage accuracy, risk stratification, and early diagnosis of such critical conditions.

Epidemiology of Diabetic-Hypertensive Emergencies

The coexistence of diabetes and hypertension markedly elevates the risk of emergency health events and hospital admissions. Globally, according to the International Diabetes Federation (IDF) Diabetes Atlas 2025, there are about 589 million adults aged 20–79 living with diabetes. In India alone, the number of adults in this age group with diagnosed diabetes is approximately, 89.8 million in 2024, placing the country as second only to China in absolute numbers.

In routine clinical series, roughly 30–50% of patients with diabetes also carry a diagnosis of hypertension, and conversely, many individuals with hypertension have clinically significant glucose dysregulation. This overlap substantially increases cardiovascular, renal, and metabolic stress in these patients. In diabetic populations globally, acute metabolic complications like diabetic ketoacidosis (DKA) and hyperosmolar hyperglycemic state (HHS) together are estimated to account for nearly 10% of hospital admissions related to diabetes, underscoring the high burden of emergent metabolic decompensation.

On the vascular side, hypertensive crises—including both "urgencies" (severe elevations in blood pressure without overt end-organ damage) and "emergencies" (with evidence of acute target organ injury)—occur in roughly 1-2% of hypertensive patients over time. Among patients with both diabetes and hypertension, these crises often coincide or are complicated by metabolic disturbances, which increases diagnostic difficulty and worsens outcomes.

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In India in particular, the burden is growing steeply. The age-standardized diabetes prevalence among adults aged 20–79 is 10.5% in 2024 in India, with projections to rise to 12.8% by 2050. Moreover, 43% of adults with diabetes in India—approximately, 38-40 million people—are estimated to be undiagnosed. Hypertension is similarly widespread; for example, a large-scale survey (NFHS-5) and other studies report that about 18% of the adult population have hypertension in some states, with co-prevalences of hypertension + diabetes even higher in older age groups.

Despite this heavy burden, early recognition in the emergency room remains a significant challenge. Many patients initially present with nonspecific symptoms — fatigue, headache, mild dyspnea, or gastrointestinal discomfort — that do not immediately suggest a metabolic-vascular catastrophe. Their biochemical findings may also be atypical or borderline (for example, modest hyperglycemia, mild acid–base disturbance, or early renal dysfunction), which further complicates and delays diagnosis. The frequent overlap of clinical and laboratory ambiguity in patients with dual pathology underscores the need for enhanced diagnostic vigilance and tools in the ER setting.

Pathophysiology of Diabetic-Hypertensive Emergencies

The convergence of diabetes and hypertension creates a pathophysiological “vicious cycle” involving endothelial dysfunction, oxidative stress, and neurohormonal activation, ultimately leading to acute metabolic and vascular decompensation. The interaction between these two chronic diseases amplifies vascular injury, impairs organ perfusion, and accelerates end-organ damage, setting the stage for life-threatening emergencies such as diabetic ketoacidosis (DKA), hyperosmolar hyperglycemic state (HHS), hypertensive crises, myocardial infarction, and stroke.

Both chronic hyperglycemia and elevated blood pressure contribute to endothelial dysfunction, a central event in diabetic-hypertensive pathology. Persistent hyperglycemia reduces nitric oxide (NO) bioavailability and increases the formation of advanced glycation end-products (AGEs). These AGEs activate nuclear factor kappa B (NF-κB)–mediated inflammatory pathways, resulting in cytokine release, vascular permeability, and microvascular injury. Similarly, hypertension induces mechanical shear stress, damaging the vascular endothelium and promoting arterial stiffness. The combination of these insults enhances prothrombotic tendencies and vascular inflammation, precipitating acute ischemic events such as stroke or myocardial infarction.[2]

In patients with coexisting diabetes and hypertension, sympathetic overactivity and renin–angiotensin–aldosterone system (RAAS) activation form a reinforcing feedback loop. Hyperinsulinemia, characteristic of insulin resistance, increases sympathetic tone and raises systemic vascular resistance. Concurrently, angiotensin II and aldosterone promote oxidative stress, sodium retention, and vascular remodeling. This neurohormonal activation aggravates hypertension and predisposes to acute hypertensive emergencies. Furthermore, the resultant vasoconstriction and endothelial damage reduce renal perfusion, heightening the risk of acute kidney injury (AKI) during metabolic or hemodynamic crises.

In insulin-deficient or insulin-resistant states, excessive lipolysis leads to the release of free fatty acids, which are converted in the liver to ketone bodies, causing metabolic acidosis characteristic of DKA. Simultaneously, osmotic diuresis leads to dehydration and intravascular volume depletion. This hypovolemic stress triggers reflex sympathetic activation, further elevating systemic blood pressure and sometimes paradoxically contributing to hypertensive crises during episodes of hyperglycemia. The interplay between dehydration, acidosis, and catecholamine surge exacerbates cardiovascular instability in emergency settings.

Both diabetes and hypertension are marked by chronic oxidative stress. Overproduction of reactive oxygen species (ROS) damages cell membranes, mitochondrial DNA, and ion transport systems. This mitochondrial dysfunction impairs cellular energy metabolism and promotes apoptosis. The resultant biochemical stress contributes to endothelial leakage, cerebral edema, cardiac electrical instability, and multi-organ dysfunction. During diabetic-hypertensive emergencies, oxidative damage amplifies tissue hypoxia and accelerates systemic decompensation.

The diabetic-hypertensive state profoundly affects cerebral autoregulation and myocardial perfusion. Even modest fluctuations in blood pressure or glucose levels can precipitate ischemic or hemorrhagic stroke, acute coronary syndrome, or heart failure. These pathophysiological interactions between the brain, heart, and kidneys create a high-risk state for multi-organ failure. In the emergency room, these overlapping pathologies manifest as complex, rapidly evolving crises that demand timely recognition and intervention.

In summary, the coexistence of diabetes and hypertension generates a multifaceted pathophysiological environment involving metabolic, hemodynamic, and inflammatory mechanisms. These intertwined processes often produce subtle or atypical clinical presentations, making early recognition challenging. AI–driven detection systems, capable of integrating dynamic, multi-organ physiological data, hold immense promise for identifying these emergencies earlier and improving patient outcomes.[3-7]

The Need for Early Detection in the ER

Timely detection of diabetic-hypertensive emergencies is of paramount importance because even short delays in diagnosis and intervention can lead to catastrophic outcomes. These emergencies often progress rapidly, resulting in multi-organ dysfunction, coma, or cardiovascular collapse if not recognized early. Conventional clinical assessment and manual risk stratification tools such as the National Early Warning Score 2 (NEWS2) and Sequential Organ Failure Assessment (SOFA) score, while useful for general critical care triage, lack the sensitivity and specificity required to capture the complex interactions between metabolic and hemodynamic disturbances in patients suffering from both diabetes and hypertension.[8]

Moreover, in the high-pressure environment of the emergency room, clinicians are faced with the challenge of integrating vast and diverse streams of patient data — including vital signs, laboratory parameters, electrocardiograms (ECG), imaging findings, and electronic health record (EHR) history — all of which evolve dynamically over time. This cognitive load often exceeds human capacity for real-time analysis, making it difficult to detect early warning signs of impending decompensation.[9]

AI, particularly through predictive analytics and machine learning algorithms, offers a transformative solution to this challenge.

AI-driven models can continuously process and interpret multi-modal patient data to identify subtle, nonlinear patterns that may precede clinical deterioration. These algorithms act as a "digital stethoscope" for the emergency physician, providing continuous risk assessment, alert generation, and early warning for diabetic-hypertensive crises. By detecting deviations from individualized baselines and correlating cross-domain data, AI tools can support timely decision-making, improve triage accuracy, and ultimately reduce morbidity and mortality in this vulnerable patient population.[10]

Overview of Artificial Intelligence in Emergency Medicine

AI refers to the simulation of human cognitive functions—such as learning, reasoning, and problem-solving—by computer systems and algorithms. In healthcare, and particularly in emergency medicine, AI has emerged as a powerful tool to enhance diagnostic accuracy, streamline workflows, and support timely clinical decisions. By processing large volumes of complex and heterogeneous patient data in real time, AI can identify patterns and correlations that may be imperceptible to human clinicians.[11]

Besides its role in medical education and rehabilitation.[12,13] In recent years, AI has been successfully integrated into several critical aspects of emergency care. For instance, automated ECG interpretation systems now assist in the rapid identification of myocardial infarction, enabling faster initiation of reperfusion therapy. Radiologic image triage algorithms facilitate the early detection of acute conditions such as stroke and intracranial hemorrhage by prioritizing critical scans for radiologist review. Sepsis prediction models, leveraging continuous electronic health record (EHR) data, can alert clinicians to early signs of infection and systemic inflammation before overt clinical deterioration occurs. Additionally, AI-powered clinical decision support systems are increasingly being used to assist with patient triage, disposition planning, and resource allocation within emergency departments.[14]

These technological advancements lay a strong foundation for the application of AI in detecting combined diabetic-hypertensive emergencies, which represent some of the most complex and rapidly evolving clinical scenarios. Such conditions require an integrated assessment of metabolic, cardiovascular, renal, and neurological parameters—an area where AI excels due to its capacity for multi-systemic data integration and predictive modelling. By extending its proven capabilities from single-system emergencies to multifactorial crises, AI has the potential to revolutionize early detection, risk stratification, and management of diabetic-hypertensive emergencies in real time, ultimately improving patient outcomes and reducing mortality.[15]

AI Applications in Diabetic Emergencies

Machine learning models that analyze real-time glucose measurements, insulin delivery records, and vital signs have shown significant promise in predicting diabetic ketoacidosis (DKA) well before its clinical manifestation.[16] By continuously monitoring dynamic physiological and biochemical parameters, these models can identify subtle deviations from normal patterns that precede acute metabolic decompensation. For example, recurrent neural networks (RNNs) trained on continuous glucose monitoring (CGM) data have demonstrated up to 90% accuracy in predicting the onset of DKA, enabling early interventions that may prevent full-blown crises. Similarly, random forest classifiers that integrate laboratory parameters—such as blood pH, serum bicarbonate, and the anion gap—can more efficiently distinguish between DKA and hyperosmolar hyperglycemic state (HHS) than traditional rule-based algorithms, aiding in rapid, precise diagnosis.[17]

Recent advances have incorporated multimodal data fusion, where AI models simultaneously process biochemical, hemodynamic, and behavioral data streams. Deep learning architectures such as convolutional neural networks (CNNs) combined with long short-term memory (LSTM) networks can capture both temporal and contextual variations in glucose trends, physical activity, and dietary patterns, further improving predictive accuracy for impending metabolic crises.[18]

AI-assisted triage systems in emergency departments now utilize decision-support dashboards that integrate electronic health record (EHR) data with bedside glucose monitors. These platforms automatically flag patients at high risk of deterioration using ensemble learning algorithms, facilitating early clinician intervention and dynamic risk stratification.[19]

Modern hybrid closed-loop systems employ reinforcement learning algorithms that "learn" individual patient responses over time, refining insulin dosing strategies based on feedback from both CGM sensors and physiological stress indicators. This personalization has demonstrated reductions of up to 30% in severe hypoglycemic episodes and improved time-in-range metrics in both Type 1 and Type 2 diabetes patients.[20]

Moreover, predictive analytics are increasingly being embedded into wearable biosensors and smartphone-based applications, allowing continuous risk assessment outside clinical settings. These digital tools can alert patients and caregivers to trends suggesting ketosis or dehydration, integrating with telemedicine platforms to trigger remote physician consultation and emergency response protocols.[21] Such integration is especially valuable in resource-limited settings, where rapid access to emergency care may be delayed.

Beyond individual management, AI is playing a growing role in population-level surveillance. Predictive epidemiological models using regional healthcare data have been developed to forecast diabetic emergency hotspots, enabling health authorities to allocate resources and optimize emergency preparedness.[22] Combined with natural language processing (NLP) algorithms applied to electronic medical records, these systems can detect unstructured indicators—such as physician notes suggesting "poor control" or "frequent admissions"—for early identification of high-risk cohorts.

By integrating predictive analytics with real-time glucose control, AI-powered systems provide a proactive approach to preventing metabolic emergencies and improving overall patient outcomes. The convergence of predictive modeling, real-time monitoring, and intelligent automation heralds a new paradigm in emergency diabetes care—one that moves from reactive management to anticipatory precision medicine.

AI Applications in Hypertensive Emergencies

Artificial intelligence models that analyze longitudinal blood pressure data, along with patient-specific comorbidities and risk factors, have demonstrated significant potential in predicting hypertensive crises before they occur.[23] By identifying subtle trends and deviations in blood pressure patterns over time, these models can alert clinicians to impending emergencies, allowing for timely intervention. For example, support vector machine (SVM) models trained on outpatient datasets have been shown to forecast hypertensive emergencies with an area under the curve (AUC) of 0.88, reflecting high predictive accuracy.[24]

Recent developments have incorporated continuous blood pressure monitoring through wearable biosensors that stream data directly to cloud-based AI platforms. These systems apply real-time anomaly detection algorithms to detect abrupt deviations or rising trends in mean arterial pressure, often several hours before the onset of hypertensive crisis. The use of federated learning models further enhances predictive robustness by allowing the algorithm to learn from diverse, multi-institutional datasets without compromising patient privacy.[25]

Beyond predicting acute blood pressure spikes, AI has been successfully applied to detect target organ damage, which is critical for distinguishing between hypertensive urgencies and emergencies. Deep learning algorithms can analyze multimodal clinical data—including fundus photographs, electrocardiograms (ECG), and chest radiographs—to rapidly identify evidence of end-organ injury such as retinopathy, left ventricular hypertrophy (LVH), or pulmonary edema.[26]

Convolutional neural networks (CNNs) trained on retinal fundus datasets can identify hypertensive retinopathy grades with accuracy exceeding 92%, outperforming human graders in early microvascular lesion detection.[27] Similarly, AI-enabled ECG interpretation platforms using deep residual networks have been validated to detect LVH and subclinical myocardial strain patterns, facilitating earlier recognition of cardiac involvement before overt heart failure.[28]

Decision-support systems powered by natural language processing (NLP) are being integrated into electronic medical records (EMRs). These systems extract unstructured clinical text—such as physician notes or triage summaries—to identify contextual cues like "severe headache", "blurred vision", or "altered mental status", which are suggestive of hypertensive encephalopathy. By combining structured vital sign data with unstructured narrative elements, these AI tools enhance diagnostic precision and reduce time-to-treatment in high-pressure emergency environments.

Furthermore, reinforcement learning-based treatment optimization algorithms are being tested to assist in the titration of intravenous antihypertensives such as nitroprusside and labetalol.[29] These models simulate multiple dosing scenarios based on patient hemodynamic responses and comorbid conditions, guiding clinicians toward individualized regimens that balance rapid blood pressure control with hemodynamic stability. AI-enabled clinical decision support systems can assist in early pharmacologic optimization by identifying patients with hypertensive emergencies complicated by acute myocardial infarction, automatically prompting the administration of high-intensity statins (e.g., atorvastatin 80 mg loading dose) in accordance with evidence-based ACS protocols, while simultaneously cross-checking for contraindications such as hepatic dysfunction or concurrent drug interactions.[30,31]

AI is also emerging as a vital component in predictive public health surveillance.[32] Machine learning models applied to regional epidemiological datasets have successfully forecasted spikes in hypertensive emergencies following extreme weather events, psychosocial stressors, or medication nonadherence trends.

By integrating predictive analytics, multimodal imaging interpretation, and adaptive therapeutic control, AI-driven systems are redefining the clinical management of hypertensive emergencies.

Integrating AI for Dual (Diabetic + Hypertensive) Emergencies

The true strength of artificial intelligence in the emergency room lies in multimodal integration, where diverse data streams are combined to provide a holistic assessment of patient status. By synthesizing information from multiple sources—vital signs, laboratory results, imaging, and electronic health records—AI can detect early warning signals of complex crises that might be missed by conventional methods.

In dual-pathology emergencies involving both diabetes and hypertension, early recognition is particularly crucial because metabolic dysregulation often precipitates vascular instability, and vice versa.[33-35] AI systems trained on multimodal datasets can identify nonlinear relationships between glucose fluctuations, blood pressure variability, and cardiac workload—patterns that may not be perceptible through routine monitoring.

Emerging "fusion AI" models employ graph neural networks (GNNs) that map interactions between multiple physiological systems—cardiovascular, renal, and metabolic—enabling real-time identification of cascading organ dysfunction.[36] Such systems can even generate probabilistic alerts with confidence scores, allowing clinicians to prioritize patients based on quantified risk levels rather than subjective impressions.

AI-assisted clinical decision support systems (CDSS) employ reinforcement learning to continuously adapt their recommendations based on real-time patient responses.[37] For example, the model may learn that a patient with elevated lactate and fluctuating systolic pressures requires concurrent glucose stabilization and vasodilator therapy, rather than a single-target approach. Such adaptive systems improve therapeutic precision and help prevent iatrogenic complications such as hypoglycemia-induced hypotension.

Integration of AI with wearable sensors and Internet of Things (IoT) devices enables continuous monitoring of critical parameters such as blood pressure and glucose.[38] These systems can automatically alert the ER team to early signs of deterioration, allowing for preemptive interventions before full-blown crises develop.

Furthermore, IoT-linked AI ecosystems can synchronize with patient smartphones or home glucometers, creating a longitudinal health trajectory that extends beyond the emergency department. Predictive cloud-based platforms can identify "at-risk" patients even before they arrive at the hospital and auto-notify emergency units through health network interfaces. This proactive coordination holds immense potential for population-scale prevention of dual metabolic-vascular crises.

In future iterations, explainable AI (XAI) frameworks are expected to enhance clinician trust by providing interpretable outputs that show which physiological trends or variables contributed most to a given risk prediction.[39] This transparency is critical for medico-legal accountability and for ensuring ethical, evidence-based adoption of AI in acute care environments. AI-driven epidemiological and predictive analytics models can screen integrated electronic health records and laboratory datasets to detect the prevalence and co-occurrence of transmissible infections such as Hepatitis B, Hepatitis C, and HIV among patients presenting with myocardial infarction to the emergency department, thereby supporting early infection control measures, personalized pharmacotherapy decisions, and safe invasive procedure planning.[40]

By bridging the gap between data-driven prediction and clinician intuition, AI integration in dual diabetic-hypertensive emergencies represents a paradigm shift from fragmented to unified emergency care.

Challenges, Limitations, and Future Directions

Despite its promise, AI implementation in diabetic-hypertensive emergency detection faces multiple challenges. Data heterogeneity across electronic health records, algorithmic bias in underrepresented populations, and integration barriers between devices and hospital systems limit real-time applicability. Ethical and legal concerns—such as patient privacy, data ownership, and medico-legal responsibility—along with the need for clinical acceptance, further hinder adoption.

Future advancements aim to address these hurdles through explainable AI (XAI), which clarifies why patients are flagged as high-risk, and federated learning, allowing model training across multiple centers without sharing sensitive data. Integration with point-of-care diagnostics and mobile health platforms may enable early community-level detection before ER admission. Ultimately, a human–machine partnership, combining AI-driven analytics with clinical judgment, promises timely recognition, risk stratification, and management of diabetic-hypertensive crises, improving outcomes while reducing emergency room burden.

CONCLUSION

Artificial Intelligence has immense potential to revolutionize emergency medicine, particularly for complex multi-morbidities like diabetes and hypertension. By detecting early warning signs through data-driven analysis, AI systems can transform emergency triage, reduce diagnostic delays, and improve outcomes. While challenges related to ethics, integration, and validation persist, the trajectory of innovation suggests that AI will soon become an indispensable ally in the early detection and management of diabetic-hypertensive emergencies.

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How to cite this article: Mani UA, Ghatak T, Sriramula N, Singh P, Yadav AR, Kumar M. Artificial Intelligence and Early Detection of Diabetic-Hypertensive Emergencies in the Emergency Room. Hypertens J. 2025;11(3):67–72.

Source of support: Nil, **Conflicts of interest:** None