International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 01 , January - 2026

The Role of Artificial Intelligence in The Diagnosis, Monitoring and Management of Anemia in CKD: A Systematic Review

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Abstract:

Background:

Anemia has a major influence on patient morbidity and mortality and is a common consequence of chronic kidney disease (CKD). Optimizing treatment outcomes is frequently not possible with traditional management techniques. Artificial intelligence (AI) has emerged as a viable method for improving the diagnosis, monitoring, and management of anaemia in CKD patients.

Objective:

To conduct a systematic evaluation of the use and efficacy of AI technologies in the diagnosis, monitoring, and management of anemia in CKD patients.

Methods:

A complete literature search was undertaken using PubMed, Scopus, and Web of Science for research published between 2010 and 2025.The inclusion criteria included research that used AI methodologies, such as machine learning, deep learning, and predictive analytics—to treat anemia in CKD. Data were retrieved and processed according to PRISMA criteria.

Results:

In total, 54 studies met the inclusion criteria. AI models revealed improved diagnostic accuracy for anemia identification, outperforming traditional approaches in terms of sensitivity and specificity. AI enabled real-time monitoring of hemoglobin levels and erythropoiesis-stimulating agent (ESA) responses. Furthermore, AI-powered prediction models enhanced ESA dosing, lowering the number of adverse events related with anemia treatment.

Conclusion:

AI has the potential to revolutionize anemia therapy in CKD by offering precise diagnosis, continuous monitoring, and individualized treatment plans. However, additional large-scale, multicenter investigations are required to corroborate these findings and ease the adoption of AI tools into clinical practice.

Keywords: Anemia, Chronic Kidney disease, Artificial Intelligence, Machine-learning, erythropoiesis-stimulating agents, Hemoglobin

INTRODUCTION:

Chronic kidney disease (CKD) is a rapidly developing multisystem condition impacting people around the world, with the biggest burden in Asia[1].Anemia is clinical condition characterized by a lack of red blood cells or hemoglobin levels that fall below a predetermined range for a person's gender and age. Anemia is diagnosed through microscopic inspection of a blood smear in PBS, which can reveal changes in RBC shape and size, as well as the presence of inclusion bodies[2].Anemia is a common consequence of chronic kidney disease.Its prevalence in CKD patients rises with disease progression, but causality remains unclear. Research suggests that CKD-related anemia may raise the risk of cognitive and sleep difficulties, as well as cardiovascular comorbidities. However, existing therapies for anemia may not entirely address these risks[3].

Anaemia in CKD results from a combination of relative erythropoietin (EPO) shortage, decreased EPO responsiveness, iron deficit, chronic inflammation, and decreased red blood cell survival[4].

The main cause of anemia in individuals with chronic kidney disease (CKD) is a reduction in erythropoietin (EPO) output. According to data from the National Health and Nutrition Examination Survey (NHANES) 2007–2010, anemia is most common in stage 5 CKD and least common in stage 1 CKD. Anemia is more likely to occur as CKD worsens. Because of symptoms including exhaustion and decreased ability to exercise, patients with CKD and anemia have a lower quality

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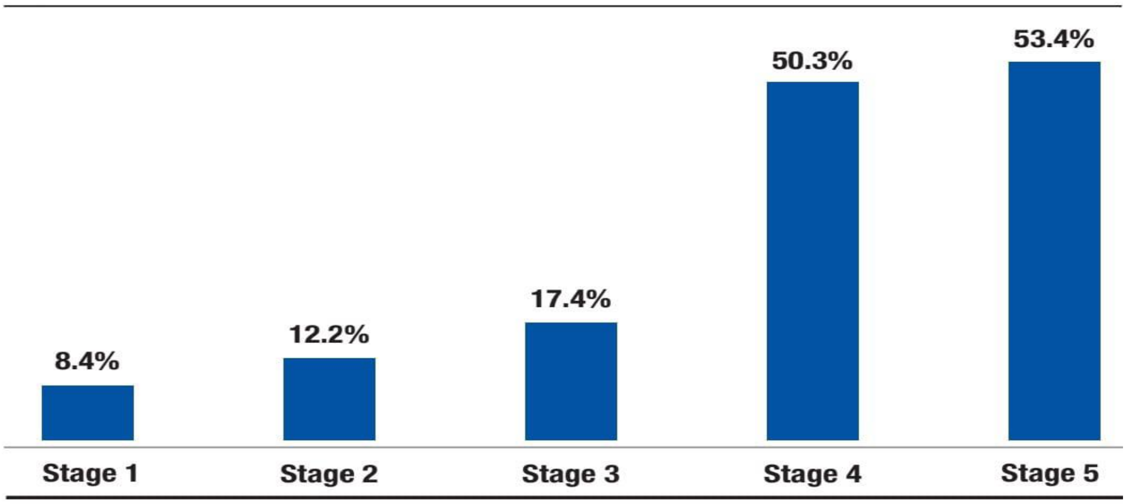
of life. In addition to increased ventricular mass, anemia in chronic kidney disease is associated with an increased risk of myocardial infarction and heart failure[5].

Figure 1.percentage of anemic individuals by stage of chronic kidney disease



Anemia is typically treated with erythropoiesis-stimulating drugs (ESAs), but individual responses vary greatly. Maintaining hemoglobin (Hb) levels within a restricted target range is crucial as low or high levels might have negative repercussions. Obtaining a target range with low fluctuation can be complex and time-consuming for clinicians[6].

Artificial intelligence [AI] is a potentially helpful tool in healthcare as more and more studies evaluate its possible applications in the context of renal illnesses.AI is defined as the science and engineering of creating intelligent computers with the ability to learn and mimic human thinking[7].

AI can be classified into two types: virtual and physical. Virtual AI encompasses information science and system-based learning, including deep learning-based symptom management to inform treatment decisions. Physical AI utilizes robots and nanotechnology to enhance medicine delivery. AI in these sectors has the potential to significantly enhance patient care[8].

Recent advances in artificial intelligence (AI) have resulted in novel techniques to diagnosing, monitoring, and managing anemia in CKD. AI technologies, particularly machine learning (ML) and deep learning (DL), have the potential to evaluate complex, high-dimensional clinical data, allowing for early identification, individualized treatment strategies, and better patient outcomes[9].

The Anemia Control Model (ACM) is a recognized medical device with an AI core that helps

with ESKD who require in-center hemodialysis (HD) and suffer from secondary anemia[10]. This software tool gives physicians dosage recommendations for effective ESA and iron therapy to keep patients' Hb and ferritin levels within the therapeutic range while reducing the need for iron supplementation and ESAs. Physicians validate ACM recommendations and, eventually, decide whether to implement them.

This review seeks to examine the present uses of AI in the treatment of CKD-related anemia, emphasizing new research and cutting-edge technologies that are influencing nephrology care in the future.

Applications of AI Anemia of CKD:

1.Diagnosis of anemia in CKD:

Traditionally,The Complete Blood Count (CBC) is the standard test for diagnosing anemia. A complete blood count (CBC) assesses the degree of anemia and involves venipuncture, qualified phlebotomists, laboratory personnel, chemical reagents, and specialized equipment. In resource-rich hospitals, findings typically take 1-4 hours. CBC collection is mostly confined to regions with competent healthcare facilities[11].

Computerized algorithms are now being used to diagnosis various diseases in medicine. AI algorithms can accurately identify anemia at a cheaper cost and in less time. AI-based anemia detection can improve efficiency by training on large datasets of patient information, including laboratory results, medical history, and clinical data, to identify patterns and predict anemia status[12].

Predictive Algorithms for early diagnosis of anemia:

Machine learning models for prediction of anemia:

Over the last decade, machine learning (ML) approaches have been increasingly applied in illness detection. This facilitates early diagnosis and increases survival rates.

Machine learning techniques include support vector machines (SVM), naive bayes (NB), decision trees (DT), k-nearest neighbors (KNN), multilayer perceptron (MLP), hybrid classifier machine learning, average ensemble (AE), genetic algorithm convolutional neural network (GA-CNN), genetic algorithm stacked encoder (GA-SAE), random forest (RF), and support vector

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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machines.machine learning techniques categorize different types of anemia,which anticipated data in the form of a complete blood count (CBC) and created a model to diagnose it[13].

The machine learning models were implemented using PyCaret,it supports many machine learning methods, including decision tree-based models (XGBoost, LightGBM, CatBoost, Random Forest, and Extra Trees) and linear models (Linear Regression, Logistic Regression, Ridge, and Lasso). PyCaret integrates these algorithms to simplify implementation. XGBoost is a high-performance machine learning algorithm that improves gradient boosting by training decision trees consecutively to rectify errors and optimize models using gradient descent. This results in fast computing, high accuracy, and resistance to overfitting. It is commonly used for regression and classification problems, especially in machine learning contests like Kaggle[14].

To identify anemia in CKD and describe how the features affect the ML model's ability to classify a patient into either anemic or not**.**

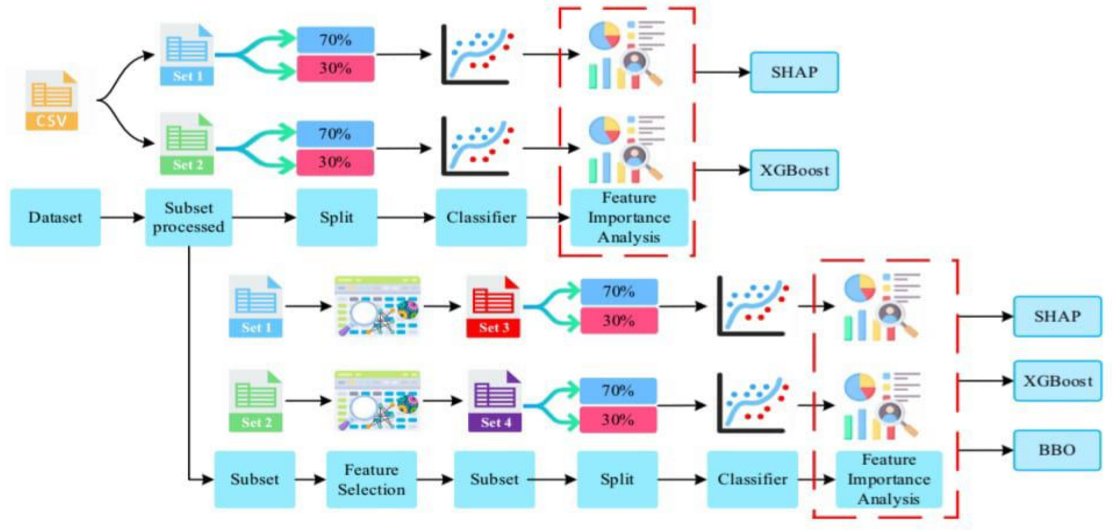

Figure.2:Working process of XGBoost

AI in image analysis:

An automated image analysis system called CellaVisionTM DM96 is used to identify and categorize the different kinds of white blood cells in peripheral blood smears. Additionally, the device can do platelet counts and partially assess the shape of red blood cells[15].

The majority of blood disorders can be diagnosed and classified with the use of this approach. Real-time communication amongst colleagues might become a natural element of the classification process, and the time spent doing differential analysis could be decreased with automatic cell location and preclassification as well as distinct cell views on the computer screen. Additionally, the workstation offers a comfortable and ergonomic workspace. it is highly recommended for routine analysis; samples from patients with malignant hematological diseases may benefit much from the system's precise morphological diagnosis[16].

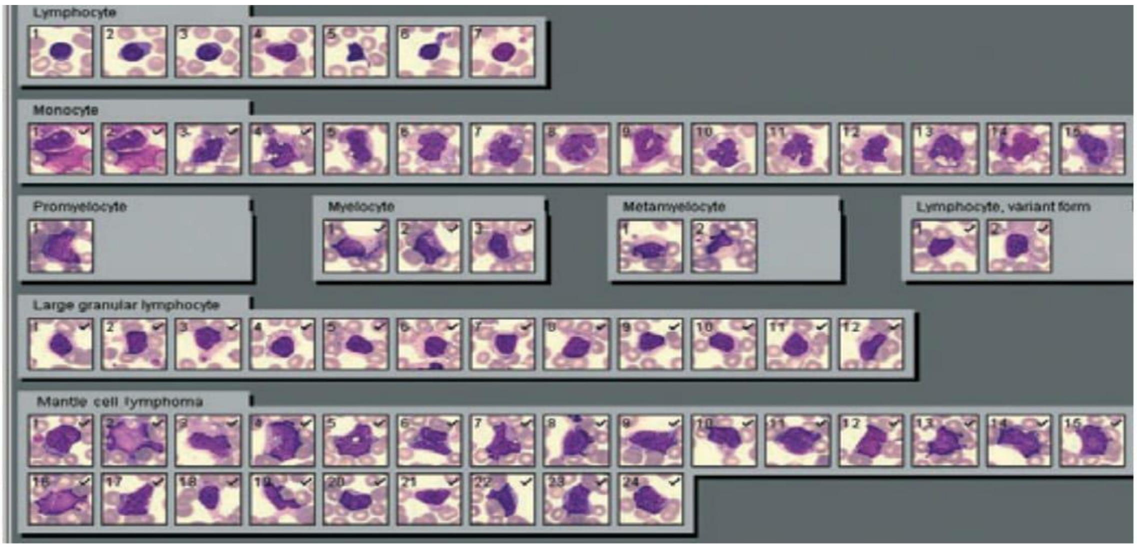

Figure-3: CNNs for blood smear interpretation:

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ISSN: 2278-0181
Vol. 15 Issue 01 , January - 2026

Blood Smear Interpretation:
A computer-aided system-deep CNN can classify red blood cells to diagnose blood diseases such as anemia.
It distinguishes between normal and aberrant morphological aspects of red blood cells, taking into account specific illnesses like anemia. Counting the quantity of contaminated RBC components and classifying anemia as moderate or chronic can aid in diagnosis. It also focused on separating the overlapping structure of RBC. Pathologists struggle to distinguish between normal and pathological shapes and sizes when there is overlap in the structure. Abnormal RBC elements' overlapping structure conceals their density and morphological characteristics (shape and size) within a unit volume[17-18].

METHODOLOGY:
The technique began by making blood smear slides.
After that, The Olympus Dp27 8.9-megapixel CMOS sensor used a small digital camera to acquire 4K resolution RBC pictures. Microscopic RBCs were captured at a resolution of 1920 x 1080. The collected photos were pre-processed and sent into a CNN-based model to detect healthy and anemic images. The model was tested on a GEFORCE RTX-3060 GPU with 12 GB of RAM, using Python 3.7 and PyTorch v1.10[19].
The methodology part consists of the following steps.

- Image collection
- Pre-processing
- Dataset arrangement
- Proposed CNN model architecture
- Loss function

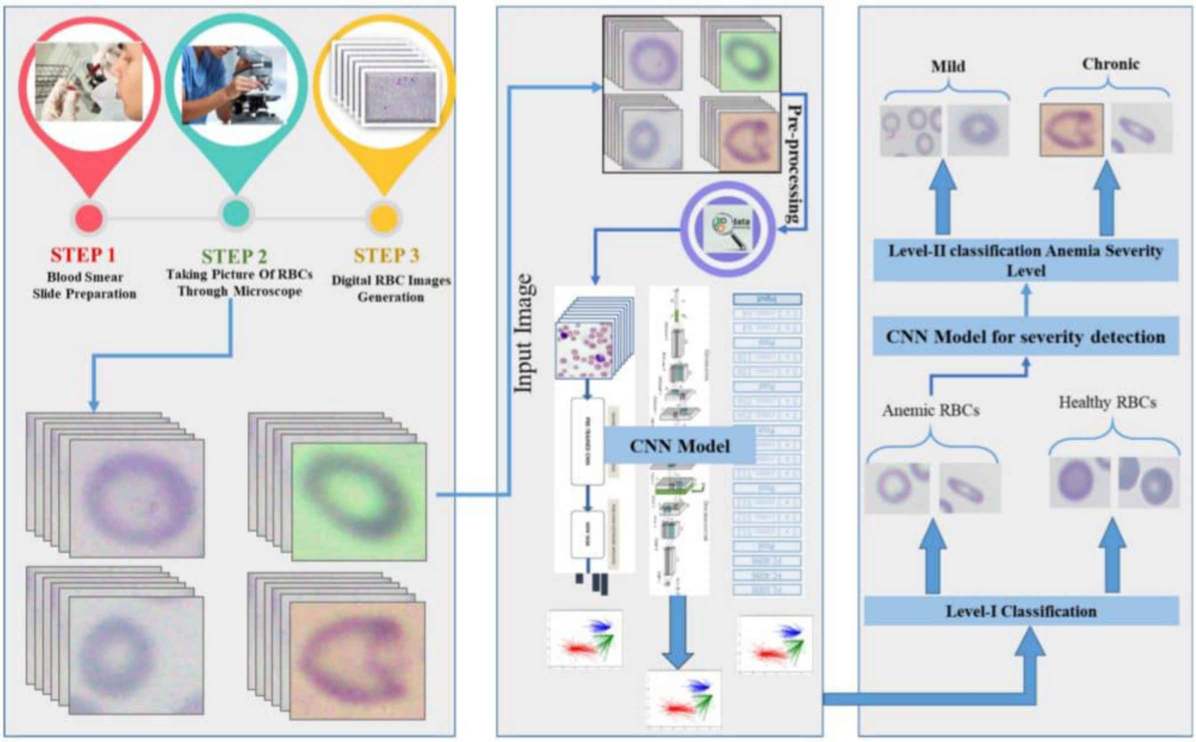

Figure.4:CNN-based model for two level classification

2. MONITORING OF ANEMIA IN CKD:

AI-based techniques have been developed to improve anemia monitoring. Barbieri and colleagues created an artificial intelligence (AI) decision support system that uses the multilayer perceptron (MLP) to monitor and treat anemia effectively[20-23].

Observing long-term changes in hemoglobin levels and individual reactions to ESA medication in the management of anemia is limited by a basic MLP. Yun et al. used a gated recurrent unit (GRU) to efficiently handle sequential data in Hb prediction and ESA recommendation tasks in order to get over these restrictions.

A GRU attention-based module (GAM). GRU-based models may overlook short-term patient state changes because to their focus on overall data distribution. The GAM, on the other hand, includes an attention module that can detect such changes. GAM predicts the eventual Hb level based on this extensive information.An alert system was introduced for RBC transfusions based on GAM data, allowing for timely intervention for critical patients[24].

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GAM captures historical data from chronic hemodialysis patients and prioritizes key information in a short duration. The GRU18 is highly efficient and effective at processing time-series data. Using a multi-head attention technique helps identify interrelationships among facts in a single window.

The patient embedding has detailed historical data on chronic hemodialysis patients. GAM generates the patient embedding using time-series data from t to t+3, including Hb levels, ESA doses, and other supplemental information. The resultant embedding is passed into the Hb predictor, which uses fully connected and dropout layers to forecast Hb levels at t+4[25].

.3. ROLE OF AI IN MANAGEMENT OF ANEMIA ASSOCIATED WITH CKD:

The process of optimizing treatment for anemia in chronic kidney disease (CKD) is intricate and dynamic, impacted by inter-individual differences in therapeutic response, complicated pathophysiology, and the requirement for ongoing monitoring[26].Erythropoiesis-stimulating agents (ESAs) are the primary treatment for anemia, their effectiveness varies by individual. Maintaining hemoglobin (Hb) levels within a small goal range is crucial, since low or high levels can lead to negative effects. Obtaining a goal range with low fluctuation is difficult and time-consuming for clinicians.Artificial intelligence (AI)-based technologies have been developed to improve anemia management.[27-28]

Artificial intelligence (AI) has become a potent tool for improving treatment precision, lowering unfavorable outcomes, and fostering individualized care[29].More accurately than traditional clinical judgment, AI-driven decision-support systems may customize therapy and forecast results by analyzing multidimensional data, including laboratory measurements, patient history, dialysis profiles, and treatment responses[30].

1.Optimization of Erythropoiesis-Stimulating Agents (ESA) Dosing

Erythropoiesis-stimulating agents (ESAs) continue to be essential in the treatment of CKD-related anemia. However, ESA therapy necessitates precise dose titration, since both insufficient and excessive dosing can be harmful. Traditional approaches frequently rely on population-based guidelines that do not account for patient-specific heterogeneity[31].

AI-Based Predictive Models for Individualized ESA Dosing:

Erythropoiesis-stimulating agents (ESAs) are central in treating anemia in CKD, but their dosing is complicated by considerable patient variability and potential risks such as hypertension, cardiovascular events, thrombosis, and excessive hemoglobin fluctuations[32].Historically, ESA dosing has relied on generalized clinical guidelines, which often fail to account for individual biological differences and dynamic clinical changes. AI-based predictive models provide a powerful solution by generating personalized dosing recommendations using complex multidimensional datasets[33].

ML algorithms include classification,prediction, pattern recognition, and clustering and feature identification.The GRU-based module, GAM, improves anemia management by recording both long-term and short-term variations in patients undergoing chronic dialysis. ESA doses can be classified into three tiers based on the patient's present status, assisting clinical specialists in making informed decisions. In circumstances of deteriorating patient conditions, it alerted to the need for RBC transfusion, allowing for timely intervention[34].An AI decision support system using MLP architecture was developed for managing anemia. However, this approach was primarily concerned with projecting Hb levels based on the patient's present situation, making it difficult to assess the patient's condition in the long run. Techniques like recurrent neural networks (RNNs)15, LSTM16, and GRU9 are used to handle sequential data and capture lengthy alterations in patient states. Yun et al.9 used multi-head attention to identify key areas of change in anemia management in patient sequential data.This method accurately catches changes in chronic dialysis patients within short durations[35].GAM provides extensive support for anemia management. It accurately captures both long-term and short-term changes in patients undergoing chronic dialysis[36].

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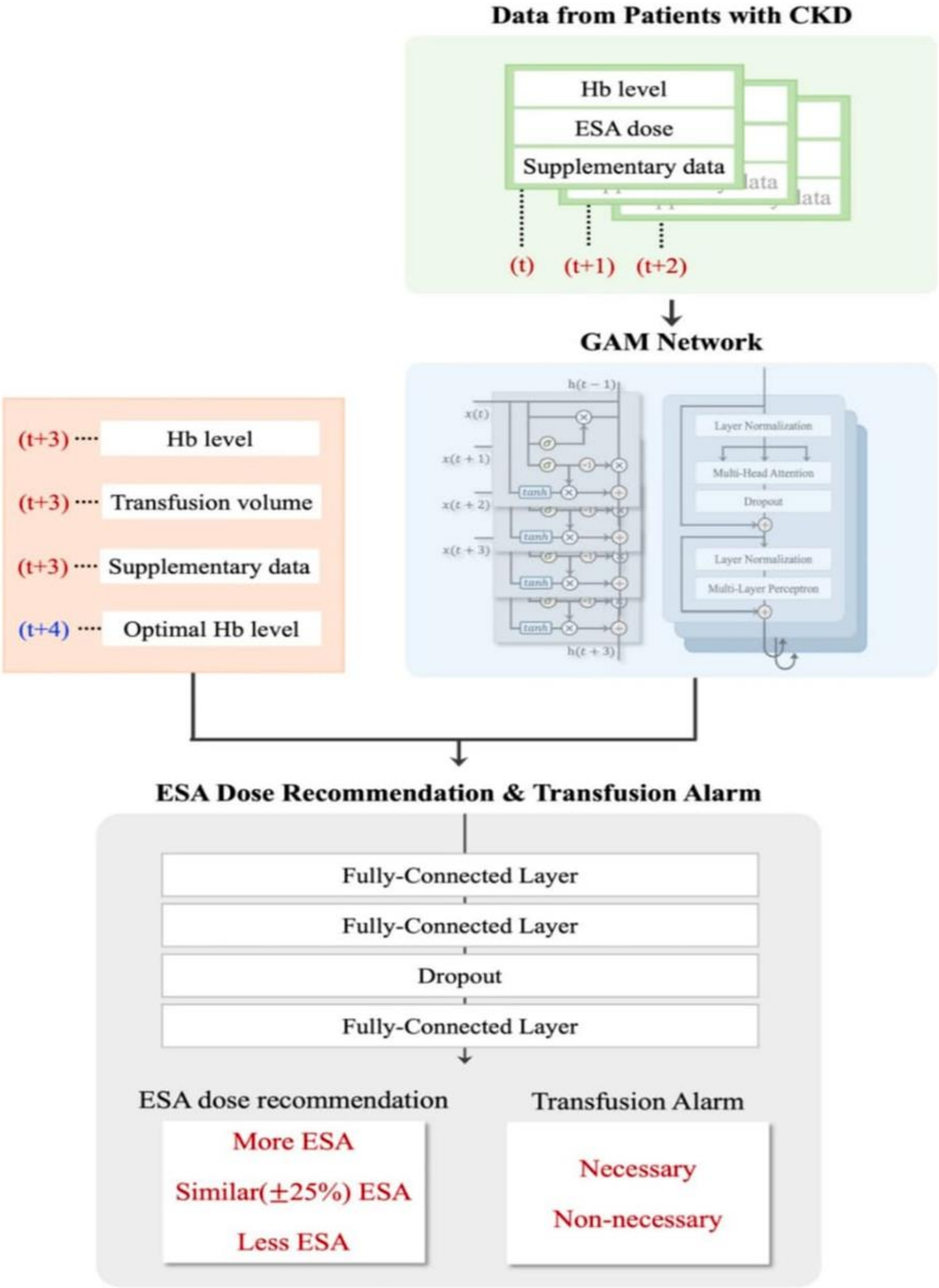

Fig-5:The framework of erythropoiesis-stimulating agents (ESA) dose recommendation and transfusion alarm process.

AI-based dosing systems outperformed traditional rule-based algorithms, such as those employed in ordinary dialysis equipment. AI-guided methods achieved tighter Hb control, fewer variations, and lower average ESA dosages in several retrospective and prospective investigations, demonstrating their promise for real-world application.

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2.AI-Assisted Iron Therapy Management:

Iron supplementation in CKD—whether intravenous or oral—is critical for supporting erythropoiesis, particularly in dialysis patients. However, iron therapy necessitates close monitoring due to hazards such as iron overload, oxidative stress, and infection susceptibility[37].AI algorithms improve iron management by anticipating iron requirements and diagnosing functional or absolute iron insufficiency earlier than traditional techniques.

AI contributions to Iron therapy:

- Predicts iron requirements based on ferritin, TSAT, CRP, dialysis adequacy, oxygenation patterns, and Hb trends.
- Identifies functional iron insufficiency, which is commonly overlooked due to complicated inflammatory connections.
- Optimizes the timing and dosage of IV iron, decreasing both deficiency and excess.
- Uses multivariate data to distinguish between iron-restricted erythropoiesis and poor ESA responsiveness[38].

Advanced models such as XGBoost and recurrent neural networks (RNNs) can simulate various clinical scenarios and recommend the best iron dose method. Early research indicates that using AI in conjunction with ESA dose prediction systems lowers unnecessary iron administration and increases ESA response[39].

3. INTEGRATION OF ESA–IRON BALANCE USING ARTIFICIAL INTELLIGENCE:

The appropriate coordination of erythropoiesis-stimulating agent (ESA) therapy with iron supplementation is crucial for efficient anemia control in CKD, as both medications are interdependent and require exact timing.Traditional clinical practice frequently struggles to maintain this equilibrium since ESA increases red blood cell synthesis, hence rapidly raising iron demand, whereas inflammation, malnutrition, and dialysis-related blood losses usually lower iron availability[40].Artificial intelligence offers a solution by combining various clinical, biochemical, and treatment-related data to calculate the best ESA-to-iron ratio for each patient. AI systems monitor hemoglobin trajectories, ESA dosing patterns, ferritin and TSAT changes, inflammatory indicators, reticulocyte counts, hepcidin levels (when available), dialysis clearance, and real-time iron use. By capturing nonlinear interactions between these characteristics, machine learning and deep learning models can anticipate when iron stocks will be insufficient to support ESA-induced erythropoiesis and prescribe prompt replenishment[41].AI, on the other hand, detects instances in which high iron storage provide a risk of oxidative stress or infection, resulting in reduced or delayed iron administration. Beyond prediction, AI-powered tools continually monitor iron and ESA dynamics, sending alerts when treatment imbalances occur—for example, increased ESA dosages despite steady ferritin, indicating functional iron deficiency, or elevated ferritin with low TSAT, indicating iron sequestration[42].This comprehensive method prevents ESA hyporesponsiveness, minimizes iron usage, and promotes stable hemoglobin management. Finally, AI transforms ESA-iron administration from a reactive to a coordinated, precision-based strategy, reducing complications, increasing therapeutic efficiency, and improving patient outcomes[43].

Anemia Control Model (ACM)

An innovative artificial intelligence (AI)-driven decision-support tool called the Anemia Control Model (ACM) was created to help nephrologists treat anemia in hemodialysis (HD) patients. Maintaining hemoglobin (Hb) concentrations within the intended therapeutic range is the major objective of the model, which combines predictive analytics and evidence-based recommendations to improve the administration of erythropoietin-stimulating agents (ESAs) and iron therapy[44].The ACM has been shown to significantly improve treatment outcomes in clinical evaluations. When the model was put into practice, the percentage of patients who achieved on-target hemoglobin values rose from 70.6% to 83.2%, Hb variability decreased, hemoglobin overshoot (Hb > 120 g/L) was reduced, and overall ESA and iron consumption decreased. Furthermore, the model resulted in decreased rates of cardiovascular events, hospitalizations, and transfusion needs, all of which are indicative of improved patient safety and therapeutic stability[45].Crucially, the ACM is not an independent prescribing system; rather, it operates solely as a decision-support tool. The attending nephrologist has the final say over treatment choices and is responsible for assessing the model's suggestions for each patient's clinical relevance, accuracy, and applicability. Thus, the combination of neural network algorithms, AI-based predictive modelling, and feedback-driven control techniques represents a major step forward for data-driven, individualized anemia management in the hemodialysis population[46].

4. GUIDING HIF-PHI (HYPOXIA-INDUCIBLE FACTOR PROLYL HYDROXYLASE INHIBITOR) THERAPY:

HIF-PHIs are a novel class of medicines that increase endogenous erythropoietin production and iron consumption. AI is rapidly being researched to guide their application[47].

Potential applications:

- Identifying early responders versus non-responders and avoiding ineffective therapy exposure[48].
- Predicting adverse events like hypertension and thrombotic risk[49].

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- ❖ Monitoring the metabolic and inflammatory cues that affect HIF-PHI efficacy[50].
- ❖ Optimizing dosage frequency based on individual hemoglobin dynamics[51].

HIF-PHIs promote greater physiologic erythropoiesis than ESAs, AI models customized to their pharmacodynamics should improve treatment personalization in the future[52].

5.Personalized Anemia Management Platforms:

The most advanced systems integrate several AI functions—diagnosis, monitoring, ESA optimization, and iron therapy prediction—into a single platform[53]

Features include:

- ❖ Real-time dashboards that monitor Hb trends and inform clinicians to any discrepancies.
- ❖ Automated decision-support systems recommend optimal ESA/iron changes.
- ❖ Predictive risk ratings based on anemia, cardiovascular health, and dialysis data.
- ❖ Patient-specific therapy routes minimize trial-and-error dosing[54].
- ❖

Some dialysis centers have tested AI-driven anemia management modules incorporated into their electronic medical records (EMRs), demonstrating:Improved time in target hemoglobin range Reduced ESA usage,Lower hospitalization rates,Increased clinician confidence and burden reduction.

CONCLUSION:

Artificial intelligence is rapidly changing the landscape of anemia diagnosis, monitoring, and management in chronic renal disease. Current review shows that AI models, ranging from traditional machine-learning algorithms to advanced deep learning and natural language processing systems, can detect anemia earlier than routine clinical workflows, identify subtle biochemical patterns, predict hemoglobin decline, and differentiate anemia subtypes with greater accuracy. AI-powered monitoring technologies allow for continuous assessment of hemoglobin trajectories, iron status, treatment response, and ESA dose requirements, minimizing variability and facilitating more tailored anemia care. Furthermore, AI-assisted decision-support systems show potential in improving treatment regimens, reducing adverse effects, and avoiding hospitalization by delivering timely, data-driven therapeutic recommendations. Although numerous models demonstrate high accuracy and predictive performance, widespread clinical implementation is still hampered by issues with data standardization, interoperability, model transparency, and integration into current healthcare systems.

ACKNOWLEDGEMENT

With great pleasure,we express our profund gratitude to faculties of Department of Pharmacy Practice,Pulla Reddy Institute of Pharmacy,Dundigal,Hyderabad.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ABBREVATIONS:

CKD-Chronic kidney disease

AI-Artificial intelligence

ESA-eryopoiesis stimulating agents

Hb-Hemoglobin

RBC-Red blood cells

CBC-Complete blood count

ESKD-End stage kidney disease

ML-Machine Learning

DL-Deep learning

ACM-Anemia control model

SVM-Support vector machine

GRU-gated recurrent unit

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