An MPL-CCN Model for Real-time Health Monitoring and Intervention

Mohammad Khaja Nizamuddin
GITAM University, Hyderabad, Telangana, India
kmohamme@gitam.edu

Syed Raziuddin
Deccan College of Engineering and Technology, Hyderabad, India
informraziuddin@gmail.com

Mohammed Farheen
Lords Institute of Engineering and Technology, Hyderabad, India
farheen0122@gmail.com

C. Atheeq
GITAM University, Hyderabad, Telangana, India
atheeq.prof@gmail.com

Ruhiat Sultana
Lords Institute of Engineering and Technology, Hyderabad, India
ruhiatsultana@lords.ac.in

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ABSTRACT

The use of Artificial Intelligence (AI) in healthcare, particularly in real-time health monitoring and predictive interventions for chronic diseases, has many benefits but also many drawbacks. Existing health risk prediction algorithms face accuracy issues and, due to the wide variety of health profiles, general algorithm applicability is problematic. The proposed model solves this issue by using an advanced AI framework to improve the accuracy of the prediction of Chronic Kidney Disease (CKD) and eliminate false positives. Our hybrid Deep Learning (DL) method blends a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN), thus including real-time feedback to help the system learn from its predictions and results. The proposed system solves a major problem in this area and sets a new benchmark for AI applications in healthcare by directly addressing prediction accuracy. It offers more tailored, accurate, and responsive chronic disease management, improving patient outcomes and healthcare resource efficiency.

Keywords-artificial intelligence; healthcare; predictive intervention; deep learning; adaptive learning systems; chronic diseases; CKD

I. INTRODUCTION

With the introduction of AI to the medical field, new standards in patient management, diagnosis, and treatment have been set, marking a watershed moment in healthcare's development. Medical researchers have been able to tap into new avenues of inquiry, enhance diagnostic accuracy, and personalize patient treatment because to AI's ability to efficiently and accurately sift through and analyze massive datasets. Utilizing intricate algorithms for early disease diagnosis and Machine Learning (ML) models for patient health outcome prediction, AI is playing a crucial and revolutionary role in healthcare, laying the groundwork for future medical breakthroughs [1]. AI has far-reaching and significant implications in the medical field. The development of AI-enhanced imaging software, which reduces human error and improves patient outcomes by accurately interpreting X-rays and MRIs, is one example of the advanced diagnostic tools made possible by this technology. AI is also driving the field of personalized medicine, which optimizes treatment strategies for individual patients by collecting and analyzing their unique health data, genetic makeup, and lifestyle [2]. In addition, chatbots and virtual assistants powered by AI are rapidly becoming an essential part of patient care. They offer round-the-clock assistance, medication reminders, and answers to health-related questions, all of which increase patient involvement and adherence to treatment plans. Despite these developments, AI application in healthcare faces many challenges. AI in healthcare relies on accurate predictions. Data biases or poor training datasets might degrade its accuracy, resulting in inaccurate diagnoses or treatment recommendations. Due to their inability to adapt to new data or patient health changes, many present AI systems are unsuitable for real-time, dynamic tasks like health monitoring and emergency response.

Regarding diabetes prediction, SVM models have been commonly utilized [3, 4]. Due to their processing cost, SVMs are not always the most efficient models for real-time prediction, especially with big datasets. Finally, SVMs may struggle with diabetes' biologically complex and non-linear feature-relationships.

Decision Trees (DTs) are among the most well-known ML tools for classification and regression. In [5], DTs were utilized to categorize people into several risk groups according to their health data, which includes age, blood pressure, cholesterol levels, smoking status, and other pertinent clinical characteristics when it comes to detecting heart diseases. DTs' key benefits are their simplicity and interpretability but have the reliability problem of being very sensitive to changes in the data, which can cause huge shifts in the tree structure [6]. Unlike DTs, the proposed uses a network of neurons that can learn complex, nonlinear data relationships without assuming feature independence.

When there are many independent variables in a dataset, Logistic Regression (LR) is a useful statistical tool for examining the relationships between them. A dichotomous variable, which can only take one of two potential values, is used to measure the outcome. LR can be employed to estimate the probabilities of Chronic Kidney Disease (CKD) progression to advanced stages given a number of variables, including age, blood pressure, serum creatinine levels, diabetes, and cardiovascular disease [7]. The model in [7] predicts the event's probability of occurrence (i.e. CKD progression) by fitting a logistic function—an S-shaped curve—to the data. A logistic (sigmoid) function is used to provide a probability score between 0 and 1, after which the input features are linearly combined by this function. Timely and focused interventions can be made possible by this score, which predicts the chance of a patient's disease developing.

Despite its popularity due to its simplicity and interpretability, LR has severe limitations in predicting CKD. Its key assumption is that the input variables and the output log probability are linear [8]. This assumption may be oversimplified for complex situations like CKD, where factors interact nonlinearly. LR cannot handle complex and non-linear associations without transforming the variables, which requires domain expertise and model complexity. Medical datasets have many related variables, which might produce predictor collinearity, which LR cannot manage [9, 10]. This restriction may distort estimates of factors' relative relevance in predicting sickness.

In this paper, an AI framework with complicated hybrid analysis and adaptive learning algorithms to address these difficulties is proposed. By tailoring health monitoring and activities to each person's health profile, this strategy enhances forecast accuracy and reliability while responding to new data. Our feedback-based algorithm improvement provides more precise, timely, and effective actions, revolutionizing customized healthcare.

The proposed DL model automatically captures nonlinear interactions among numerous factors, eliminating the need to manually convert features. DL networks handle complex and non-linear interactions better by automatically learning the optimum data representation for prediction. This talent improves our prediction and clinical decision-making by helping us understand CKD condition. DL's data-processing and learning skills allow the model to adapt to new input and improve its predictions [11]. Our DL algorithm can automatically generate hierarchical data representations, making it better than SVMs at detecting intricate and non-linear feature correlations. DL algorithms, especially multi-layered ones, can process and integrate many health indices to capture the complex patterns and interactions that define diabetes development and progression. This allows more exact and personalized projections because diabetes presents differently in each person. DL models are more dynamic and scalable than SVMs and can handle larger datasets. Logistic Regression for CKD Progression

II. THE PROPOSED SYSTEM

In healthcare, AI is set to redefine real-time health monitoring and predictive interventions for chronic diseases. Traditional methods falter due to their simplistic assumptions and a generalized approach that fails to account for individual variability. These shortcomings manifest in inaccuracies and the inability to precisely predict health risks, resulting in either unnecessary anxiety or overlooked conditions due to false positives and negatives. Moreover, the diversity of individual health profiles presents a significant challenge for the universal applicability of predictive algorithms. Our proposed model leverages an advanced AI framework, employing a hybrid DL strategy that synergizes patient-specific data with broader health trends, aiming to significantly enhance prediction accuracy and minimize false alerts.

$$Risk\ Prediction\ Error = \frac{1}{N}\sum_{i=1}^{N}(Predicted\ Risk_i - Actual\ Risk_i)^2 \quad (1)$$

$$False\ Positive\ Rate = \frac{FP}{FP+TN} \quad (2)$$

$$False\ Negative\ Rate = \frac{FN}{FN+TP} \quad (3)$$

To circumvent the limitations of conventional models like LR, which simplifies the intricate dynamics of variables into a linear relationship, our approach adopts DL, which excels in identifying complex, nonlinear interactions among variables, offering a deeper understanding of disease progression. The proposed DL model capitalizes on multiple layers of neural networks, employing activation functions such as the Rectified Linear Unit (ReLU) to process data, effectively capturing the nuanced relationships within the health data.

$$ReLU(x) = \max(0, x) \quad (4)$$

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \quad (5)$$

$$Loss\ Function = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(y'_i) + (1-y_i)\log(1-y'_i)] \quad (6)$$

The dataset of clinical records undergoes rigorous preprocessing, including normalization to ensure uniformity across the feature set $\left(X' = \frac{X - X_{min}}{X_{max} - X_{min}}\right)$. Feature selection harnesses techniques like mutual information to discern the most predictive variables for CKD, while feature engineering generates new features capturing complex disease progression patterns.

$$Normalized\ Feature = \frac{Feature - Feature_{min}}{Feature_{max} - Feature_{min}} \quad (7)$$

$$I(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y) log\left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (8)$$

$$Engineered\ Feature = \frac{Feature_A}{Feature_B + \epsilon} \quad (9)$$

The model's architecture is well-thought-out; it uses a Multi-Layer Perceptron (MLP) with ReLU activation functions to render linearity non-existent and overfitting prevention layers to avoid it. The model is fine-tuned for prediction by training it on a large dataset and then uses the Adam optimizer to reduce the binary cross-entropy loss. By incorporating a real-time feedback mechanism into its continuous learning process, AI is able to adapt and evolve, leading to healthcare interventions that are both tailored and timely. Our proposed model employs a hybrid DL approach consisting of a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN). The model architecture includes an input layer that receives patient data, followed by multiple hidden layers with ReLU activation functions to capture complex non-linear relationships. The MLP component handles structured data, while the CNN processes sequential health records. The final layer uses a sigmoid activation function to output a probability score indicating the likelihood of a chronic disease. This probability score (0 to 1) helps in classifying the patient's health status as either diseased or healthy.

$$Model\ Architecture = Input\ layer + \sum(Hidden\ Layers) + Output\ Layers \quad (10)$$

$$Dropout\ Rate = \frac{Number\ of\ Dropped\ Neurons}{Total\ Neurons} \quad (11)$$

$$Adam\ Optimizer\ Loss\ Minimization = min\left(-\frac{1}{N}\sum_{i=1}^{N}[y_i \log(y'_i) + (1-y_i)\log(1-y'_i)]\right) \quad (12)$$

A data-driven healthcare strategy is encapsulated by the CKD predictive modeling algorithm. The algorithm quantifies the divergence between the model's projected outcomes and the actual patient data, starting with the Binary Cross-Entropy Loss function. The training phase would not be complete without this loss function, which serves as a foundation for the predictive model by penalizing it for errors and gradually improving its accuracy. In order to achieve a more gradual convergence, the model parameters are iteratively updated using the Adam optimization rule. This algorithm is quite complex. It modifies the neural network's weights in order to minimize the loss function, considering both the parameter gradients and the momentum of prior updates.

The model then uses the sigmoid activation function to provide predictions, which indicate the chance of CKD progression in a patient as a probability between 0 and 1. Wherever the model's predictions differ from the anticipated results, a Feedback Adjustment phase is utilized. Important for the model's error-reduction capabilities, this stage involves shifting weights in a way that improves future predictions. The Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC) assesses the model's ability to discriminate between classes; it is one of the metrics computed to assess the model's performance. Additionally, we calculate the model's sensitivity to learn about its performance with respect to genuine positive rates and specificity to learn about its capacity to avoid false positives. In the medical industry, where both false positives and negatives can have serious implications, the F1 Score plays a vital role in achieving a balance between sensitivity and precision, which is measured by the accuracy of the model's positive predictions.

Proposed Algorithm:

Step 1:

$$Binary\ Cross - Entropy\ Loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(y'_i) + (1-y_i)\log(1-y'_i)]$$

Step 2: $Adam\ Update\ Rule = \theta_{next\ step} = \theta_{previous\ step} - \mu.\nabla_\theta J(\theta)$

Step 3: $Model\ Prediction = \sigma(W.X + b)$

Step 4: $Feedback\ Adjustment = W_{new} = W_{old} + \alpha.(Target\ Output - Model\ Output).X$

Step 5: $Model\ Evaluation\ Metric = \frac{1}{n}\sum_{i=1}^{n} I(y'_i = y_i)$

Step 6: $Sensitivity = \frac{TP}{TP+FN}$

Step 7: $Specificity = \frac{TN}{TN+FP}$

Step 8: $Precision = \frac{TP}{TP+FP}$

Step 9: F1 Score=2.$\frac{Precision\ .\ Sensitivity}{Precision+Sensitivity}$

Step 10:

$$Model\ Update\ Frequency = \frac{Number\ of\ Epochs}{Improvement\ Threshold}$$

Step 11: $Data\ Augmentation = X_{aug} = f(x)$

Step 12:

$$Hyperparameter\ Tuning = \arg min_\lambda Validation\ loss(\lambda)$$

Step 13:

$$Regularization\ Technique\ Aplication = \lambda \sum_{i=1}^{n} \theta_i^2$$

Step 14:

$$Model\ Deployment\ Rediness\ Score = \frac{Number\ of\ Successfull\ Predictions}{Total\ Preditions}$$

Step 15:

$$Continous\ Monitoring\ Metric = \frac{Sum\ of\ deviations\ in\ Predictions\ over\ time}{Number\ of\ Predictions}$$

Step 16:

$$Patient\ Outcome\ Improvement\ Rate = \frac{Number\ of\ Improved\ Outcome\ Post\ Interventions}{Total\ interventions}$$

In addition to these core performance metrics, the algorithm also factors in Model Update Frequency to determine how often it needs retraining to maintain its accuracy as new data becomes available. This is a pragmatic approach in the rapidly evolving field of healthcare where patient data and disease patterns can change over time. Data augmentation is conducted to artificially expand the dataset, which helps in improving the model's robustness by providing a more varied set of scenarios for the model to learn from.

The subsequent steps introduce advanced strategies to refine the model further. Hyperparameter tuning is utilized to find the optimal settings for the model's parameters that lead to the best performance on the validation dataset, a crucial step to prevent overfitting and to ensure that the model generalizes well to new, unseen data. The regularization technique application is another safeguard against overfitting, penalizing the complexity of the model by adding a regularization term to the loss function, which helps in the development of a more generalized model.

A unique aspect of this algorithm is the consideration of a Model Deployment Readiness Score, which assesses whether the model is performing at a level suitable for real-world application. This ensures that only well-performing models are deployed in clinical settings, safeguarding patient care. Once deployed, Continuous Monitoring Metrics are utilized to track the model's performance over time, ensuring that any degradation in accuracy is swiftly identified and addressed. Finally, the algorithm calculates the Patient Outcome Improvement Rate, directly correlating the model's predictions with patient health outcomes to quantify the model's impact in practical terms. This rate is a direct measure of the model's efficacy in contributing to improved healthcare interventions and patient care.

In summary, the algorithm provides a detailed framework for the development, evaluation, and deployment of a deep learning model for CKD prediction. It meticulously balances the technical aspects of ML, such as loss functions and optimization algorithms, with the practical needs of healthcare delivery, such as sensitivity to patient outcomes and adaptability to new data. The resulting model promises not only to enhance the predictive accuracy in healthcare settings but also to evolve continuously in response to an ever-changing medical landscape, driving forward the potential of AI to deliver personalized, responsive care and to improve patient outcomes significant. The sample dataset used for proposed model is represented in Table I.

TABLE I. THE SAMPLE DATASET USED IN THE PROPOSED MODEL

Age	58	48	34	45	29	56	38	43	49
Gender	F	M	F	M	F	F	M	F	M
BP	162	145	111	160	110	162	135	121	159
Albumin	1	3	0	2	4	2	3	2	1
Sugar	1	5	2	0	3	1	4	3	1
Blood urea	71	18	45	55	16	69	34	43	65
Serum creatinine	1.87	4.75	1.03	2.93	3.24	2.87	4.65	3.43	4.33
Hemoglobin	14.76	13.07	10.21	16.45	8.35	12.76	15.37	14.22	15.63
Hypertension	No	Yes	No	No	Yes	No	Yes	Yes	No
Diabetes mellitus	No	No	No	Yes	Yes	No	No	No	Yes
Appetite	Good	Good	Poor	Poor	Good	Good	Good	Poor	Poor
Pedal edema	No	No	Yes	Yes	No	No	No	No	Yes
Anemia	No	Yes	No	Yes	Yes	No	Yes	No	Yes
Sodium	140.2	141.4	131.9	132.7	139.6	163.1	153.4	121.9	137.8
Potassium	5.42	3.91	4.68	4.91	5.14	6.32	8.54	3.73	5.12
Score	0.323	0.732	0.445	0.575	0.612	0.387	0.723	0.494	0.634
Class	No CDK	CDK	No CDK	CDK	CDK	No CDK	CDK	No CDK	CDK

III. RESULTS

With a special emphasis on CKD, our AI framework, built around a DL architecture, has been painstakingly modified to meet the demands of real-time health monitoring for chronic illnesses. The model claims to greatly improve forecast accuracy and decrease false alarms by using a hybrid approach that combines patient-specific data with large population health trends. It has an adaptive learning process that is driven by real-time feedback, so the model can continuously improve its predictions based on the results of its interventions. The proposed model was compared to two popular methods in the domain, the standard LR model and the RF algorithm. The complicated, non-linear correlations common in medical data might be difficult for LR to handle, despite its popularity in medical statistics due to its interpretability and simplicity. In contrast, RF provides stronger performance by combining numerous DTs to better manage non-linearity; yet, it could not have the same level of dynamic adaptability as DL models. Figure 1 shows the proposed model's performance and its comparison to RF and LR, vs the number of epochs. Gains in Area Under the Curve (AUC) over time shows that the proposed model performs better than the competition. The logarithmic growth in the precision score of the proposed model in Figure 2 shows that it improves quickly at first, but then at a slower rate as it refines its prediction abilities. The RF model displays moderate growth and the LR model indicates a more modest increase. The recall graph in Figure 3 portrays a similar scenario, with the proposed model starting with a high score and witnessing minor but constant improvements. Both LR and RF models start lower and progress more gradually, with RF surpassing LR but not achieving the performance of the proposed model.

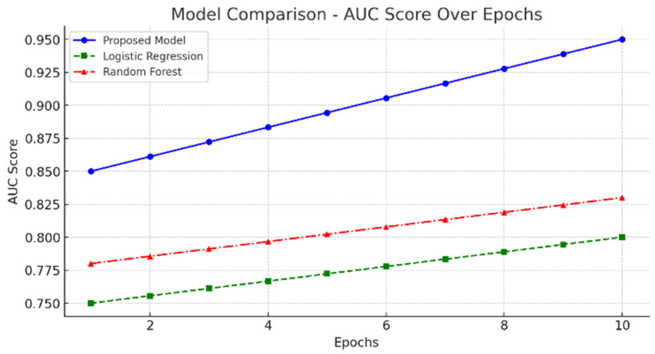

Fig. 1. Accuracy comparison between the proposed model, RF, and LR.

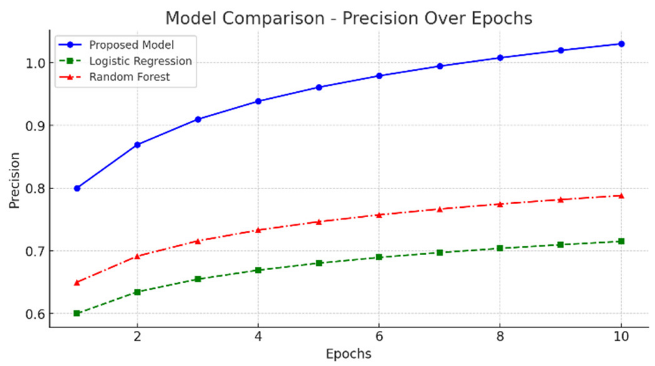

Fig. 2. Precision comparison between the proposed model, RF, and LR.

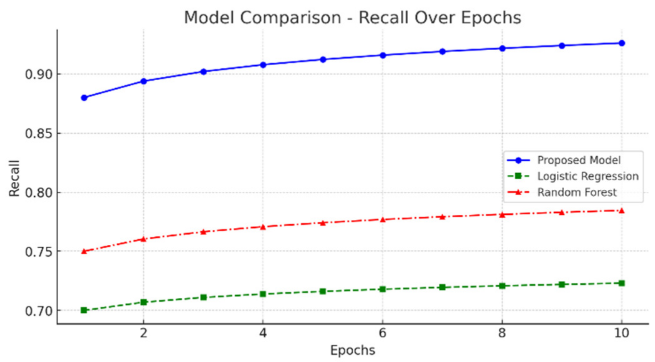

Fig. 3. Recall comparison between the proposed model, RF, and LR.

IV. CONCLUSION

Addressing a significant knowledge gap in chronic disease management, this study presents an innovative AI model designed to enhance predictive accuracy and patient outcomes. The proposed AI model significantly enhances chronic disease management through its advanced predictive capabilities. Compared to more traditional approaches, such as Logistic Regression and Random Forest, the suggested AI model performs better across a number of important measures, establishing a new standard for real-time health monitoring. It has the potential to completely transform patient care with its advanced deep learning framework, which greatly improves the accuracy of predictions for chronic diseases like CKD. The model exemplifies the power of machine learning in healthcare by reliably outperforming traditional methods in terms of both recall and precision.

In conclusion, this work not only fills a crucial gap in predictive healthcare but also introduces a novel application of deep learning in chronic disease management. By outperforming existing models in precision and recall, our AI model sets a new benchmark for future research. This demonstrates how AI has the ability to revolutionize healthcare by improving both patient outcomes and system efficiency. In the future, these models will be essential in creating healthcare solutions that are more proactive and tailored to each individual's needs.

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