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Chronic Kidney Disease Prediction Using Deep Neural Network Architectures: A Comparative Study of ANN and CNN Approaches

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***Abstract*—Chronic kidney disease (CKD) is a major public health problem that requires early and accurate diagnosis for ef- fective treatment. This project compares a Convolutional Neural Network (CNN) and an Artificial Neural Network (ANN) for the prediction of Chronic Kidney Disease (CKD) using clinical and laboratory data. Both models undergo preprocessing, including missing value handling, normalization, oversampling for class imbalance, and feature selection. CNN uses convolutional layers for pattern recognition, while ANN uses a simpler architecture with selected features. The performance of the model is evaluated using accuracy, confusion matrices and classification reports. The study aims to identify the most effective approach for pre- dicting CKD, improving early diagnosis and optimizing patient outcomes.**

***Index Terms*—Artificial neural network, convolutional neural network, chronic kidney disease, machine learning**

I. Introduction

Kidney disease (CKD) is a progressive disease characterized by the gradual loss of kidney function, often leading to serious health complications and a reduced quality of life. Early detection and accurate diagnosis of CKD are crucial in order to take timely medical action and prevent further deterioration. In recent years, advances in machine learning have enabled the development of predictive models that can analyze complex clinical and laboratory data to support the diagnosis of CKD. This project aims to investigate and compare two machine learning approaches: Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN). CNNs are typically used for image data and are suitable for reshaped feature data due to their ability to capture local patterns. On the other hand, ANNs are often used to analyze structured data due to their straightforward architecture and flexibility in processing smaller feature sets.

By pre-processing the dataset to handle missing values, nor- malize features and remove class imbalance through oversam- pling, the models are trained and tested on a refined dataset. Feature selection is performed with ExtraTreesClassifier, while principal component analysis (PCA) is used for dimensionality reduction.

The main objective of this study is to evaluate the effective- ness of both models in predicting CKD and compare their per- formance using metrics such as accuracy, confusion matrices and classification reports. The results of this comparison will provide valuable insights into the suitability of these models or clinical applications and ultimately contribute to advances in predictive medicine technology.

II. Literature Survey

A. *Paper Title: Chronic Kidney Disease Prediction Based on Machine Learning Algorithms. Authors: Md. Ariful Islam, Md. Ziaul Hasan Majumder, Md. Alomgeer Hussein. Year of Publication: 2023*

*Description:*The study investigates the use of machine learning algorithms for the early detection of chronic kidney disease (CKD), a global health problem that often progresses unnoticed to more advanced stages. To improve diagnostic accuracy, the study examines the relationships between data factors and CKD features using predictive modeling. The study used a dataset of 400 examples from the UCI Machine Learning Repository, which contained 24 attributes associated with patient health measures. To increase efficiency and reduce dimensionality, principal component analysis (PCA) was used. After applying PCA, XGBoost had the highest accuracy of (99.16%) among the 12 machine learning classifiers tested in the study.

*Methodology:*The CKD dataset was pre-processed as part of the procedure to fill in missing values and to code categorical variables. PCA and Recursive Feature Elimination (RFE) were used to find the most important features for CKD diagnosis. Metrics such as accuracy, precision, recall and F1 score were used to evaluate the classifiers after dividing the dataset into a training (70%) and a test (30%) group. Sophisticated methods such as stratified cross-validation were used to reduce overfitting and optimize model parameters. The classifiers used included XGBoost, AdaBoost, Random Forest and Gradient Boosting, whose remarkable performance proved their appli- cability to structured data.

*Limitations:*The study was mainly limited by the small size of the data set (400 cases), which could affect the transferability of the results. In addition, the dependence of the data set on certain characteristics makes it difficult to generalize the results to larger populations or to compare the results with other data sets. Other limitations to the robustness of the proposed models include the lack of external validation using a large number of data sets.

B. ***Paper Title: Prediction of Chronic Kidney Disease Using Machine Learning. Authors:Md Nayeem Hosen, Md Ariful Islam Mozumder, Rashedul Islam Sumon,Hee-Cheol Kim. Year of Publication: 2023***

Description: The research focuses on the rise in the number of patients suffering from chronic kidney disease. Kidney replacement and dialysis incur the most cost so it is better to predict the disease at the earliest. So to overcome this a prediction model was developed using machine learning techniques like Support Vector Machine (SVM), Random Forest(RF), and Artificial Neural Network (ANN). Training these algorithms was done with the help of the UCI repository.
*Methodology:*The classifiers performance metrics was measured through parameters like precision, recall, f- score,and accuracy by splitting the data into 70% for training and 30% for testing. After inputting the datasets it undergone several preprocessing techniques to improve accuracy and it is applied to three different classifiers and got CKD prediction using soft voting ensemble method. ANN model outperformed the other two models with an accuracy of about 98.61%.
*Limitations:*Limitations include reliance on a single dataset, which may not generalize across diverse populations or conditions. Future work could involve validating these models on larger and more varied datasets to ensure robustness.

C. ***Paper Title: Prediction of Chronic Kidney Disease- A Machine Learning Perspective. Authors:Pankaj Chittora, Sandeep Chaurasia, Prasun Chakrabarti, Gaurav Kumawat, Tulika Chakrabarti, Zbigniew Leonowicz, Micha Jasi Ski, Ukasz Jasi Ski, Radomir Gono, Elbieta Jasi Ska, Vadimbol-shev. Year of Publication: 2023***

Description: This article focuses on chronic kidney disease, which is one of the most critical diseases today and for which correct diagnosis and early prediction is necessary.The study uses a dataset from the UCI repository to predict chronic kidney disease (CKD) using machine learning models. Various feature selection techniques and classification algorithms were used to increase prediction accuracy. Performance metrics such as accuracy, precision, recall, F-measure and AUC were used to evaluate the models.
Methodology: For this purpose, 400 cases and 24 attributes from the CKD dataset of the UCI are used. The data set is pre-processed using various methods, including binary transformation, normalization, and the treatment of missing values. Features are selected using LASSO regression, the wrapper method, and correlation-based feature selection (CFS). Machine learning models such as Random Tree, LSVM, KNN, logistic regression, C5.0, CHAID and Applied ANN were used. Deep Neural Network (DNN) was used for additional comparisons.
*Limitations:*The generalizability of the results could be affected by the small size of the data set of 400 instances. Only one deep learning architecture was examined.

D. ***Paper Title: ML-CKDP: Machine learning-based chronic kidney disease prediction with smart web application. Au-thors: Rajib Kumar Halder,Mohammed Nasir Uddin, Md. Ashraf Uddin, Sunil Aryal, Sajeeb Saha, Rakib Hossen, Sabbir Ahmed, Mohammad Abu Tareq Rony, Mosammat Farida. Year of publication: 2024***

*Description:*The article deals with the ML-CKDP model, which uses machine learning to predict chronic kidney disease (CKD). The two objectives are to improve data preprocessing for CKD classification and to develop a user-friendly, webbased application for real-time CKD prediction. The study uses seven classifiers, including Random Forest (RF) and AdaBoost (AdaB), which achieved 100% accuracy on different validation methods. The web application aims to make CKD prediction accessible and cost-effective, especially in resourceconstrained environments.
*Methodology:*The methodology of the study is divided into several important steps. First, data preprocessing is performed, in which categorical variables are converted into numerical values using label coding, missing values are underlaid with mean values, and data are normalized using min-max scaling to ensure uniformity. Next, feature selection is performed using advanced techniques such as correlation, chi- square, variance thresholding, recursive feature elimination, sequential forward selection, lasso regression and ridge regression. These methods are combined to increase the robustness of the model by utilizing the unique strengths of each technique. Subsequently, classification is performed using seven machine learning algorithms: Random Forest (RF), AdaBoost (AdaB), Gradient Boosting (GB), XgBoost (XgB), Naive Bayes (NB), Support Vector Machine (SVM) and Decision Tree (DT). The performance of the classifiers is rigorously validated by trainingtest splitting and k-fold cross-validation to ensure reliability and generalizability. Evaluation metrics such as accuracy, area under the curve (AUC), confusion matrices and time spent on training and testing are used to comprehensively evaluate the performance of the models. Finally, a web application using Flask will be developed to operationalize the prediction model. The user-friendly application allows relevant data to be entered via a web portal, which generates a CKD diagnosis as ”positive” or ”negative” and provides the option to print the results for further consultation. This integrated methodology ensures the accuracy, accessibility and practicality of the model.
*Limitations:*The study acknowledges several limitations that could affect the effectiveness and applicability of the proposed model. Among the problems with the dataset is its relatively small size, containing only 400 instances, which could limit the generalizability of the model to broader populations. In addition, the presence of missing values and categorical variables requires extensive pre-processing, making the workflow even more complex. Algorithms are limited for classifiers such as Naive Bayes and Support Vector Machine

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(SVM), which showed lower performance on certain datasets. In addition, ensemble methods such as Random Forest (RF) and Gradient Boosting (GB) have higher time complexity, which makes them less suitable for scenarios that require fast predictions. In terms of practical challenges, real-world CKD datasets often contain noisy or incomplete data, which can affect the robustness of the model. Furthermore, economic and infrastructural constraints in developing regions may hinder its widespread use despite the cost-effective design of the web application. These limitations point to areas that need further refinement to improve the scalability and practical applicability of the model.

III. Proposed Methods

The proposed system for Chronic Kidney Disease (CKD) prediction integrates a comprehensive data engineering pipeline with advanced deep learning models—Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). The methodology consists of several stages:

A. *Data Preprocessing*

- **Missing Value Imputation:** Numerical features with missing values are imputed using mean substitution.
- **Categorical Encoding:** Features such as 'rbc', 'pc', and 'htn' are label-encoded into numeric binary values.
- **Normalization:** Min-Max scaling is used to transform numerical features to the [0,1] range.
- **Class Balancing:** The RandomOverSampler technique is used to oversample the minority class and balance the dataset.

B. *CNN-Based Prediction Pipeline*

- **Input Reshaping:** Feature vectors are reshaped into a 2D matrix (e.g., 6×4) suitable for CNN input.
- **Convolutional Layers:** Apply filters to extract spatial dependencies among features.
- **Pooling Layers:** MaxPooling reduces spatial dimensions, retaining essential features.
- **Flattening and Dense Layers:** After flattening, the data passes through dense layers.
- **Activation Functions:** ReLU in hidden layers, sigmoid in the output layer.
- **Loss and Optimizer:** Binary cross-entropy loss and Adam optimizer.

C. *ANN-Based Prediction Pipeline*

- **Input Layer:** Directly accepts flattened feature vectors.
- **Hidden Layers:** Consist of fully connected layers with ReLU activations.
- **Output Layer:** Single sigmoid-activated neuron for binary classification.
- **Training:** Uses binary cross-entropy and Adam optimizer with early stopping.

D. *Evaluation and Deployment*

- **Metrics:** Accuracy, Precision, Recall, F1-score, and Confusion Matrix.
- **Visualization:** Training and validation curves are plotted to evaluate learning behavior.
- **Serialization:** Final models and preprocessing steps saved using Joblib for deployment.
- **Interface:** Integrated into a Streamlit-based frontend for real-time clinical use.

IV. Algorithms Used

The proposed system utilizes two primary deep learning algorithms—Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN)—for the prediction of Chronic Kidney Disease (CKD) using clinical data. Both models are implemented with distinct design philosophies, tailored to exploit the structure of the input data while maximizing prediction accuracy.

The Artificial Neural Network (ANN) is a feedforward model inspired by the structure of biological neurons. It consists of an input layer that receives 24 processed fea- tures, including both numerical clinical metrics and encoded categorical values. These inputs are passed through a series of fully connected hidden layers that employ the Rectified Linear Unit (ReLU) activation function, which introduces non- linearity and enables the model to capture complex interactions among the features. The final layer of the ANN is a single neuron activated by the sigmoid function, which produces a probability output indicating the likelihood of CKD presence. The model is trained using binary cross-entropy as the loss function and the Adam optimizer, which adapts the learning rate for efficient convergence. To mitigate overfitting, early stopping is employed based on validation loss, ensuring that training halts when no further performance improvements are observed.

The Convolutional Neural Network (CNN), although typi- cally designed for image data, is adapted here to handle struc- tured clinical data by reshaping the input features into a two-dimensional grid (e.g., 6×4 matrix). This transformation allows the CNN to leverage its convolutional layers to detect local patterns and feature interactions that may represent underlying physiological relationships among variables. The CNN archi- tecture begins with one or more convolutional layers that apply learnable filters across the reshaped input matrix, generating feature maps that emphasize relevant patterns. These maps are then passed through pooling layers, such as MaxPooling, which reduce dimensionality and enhance computational effi- ciency while retaining dominant features. The output from the pooling layers is flattened and fed into fully connected dense layers, culminating in a sigmoid-activated output neuron for binary classification. Like the ANN, the CNN is also trained using binary cross-entropy and optimized using Adam. The combination of local feature extraction and non-linear learning enables the CNN to outperform traditional models even on structured, non-visual data.

In comparison, both ANN and CNN demonstrated excellent performance in predicting CKD. However, the CNN model

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consistently outperformed the ANN, achieving perfect scores in accuracy, precision, recall, and F1-score. This performance difference is attributed to CNN's ability to capture local spatial relationships among features, even when applied to tabular data. While the ANN model remains a strong and efficient choice for structured input, the CNN's adaptability and robust pattern recognition capabilities make it a superior candidate in this application. Thus, the integration of both models provides a comparative foundation for selecting optimal neural architectures in clinical predictive systems.

V. Data Flow Architecture

The data flow in the proposed CKD prediction system follows a structured pipeline designed to ensure data integrity, model accuracy, and seamless user interaction. Each stage plays a crucial role in transforming raw clinical input into actionable disease predictions. The stages are outlined as follows:

A. *1) Data Collection*

The pipeline begins with the acquisition of raw patient data. This may include numerical clinical metrics (e.g., blood pressure, serum creatinine, hemoglobin) and categorical inputs (e.g., presence of diabetes, hypertension, or edema). These values are collected either manually via user input in the frontend or fetched from existing clinical databases.

B. *2) Data Preprocessing*

Raw data is passed through a robust preprocessing module which performs:

- **Imputation:** Missing values in numeric fields are filled using mean values to maintain consistency.
- **Encoding:** Categorical features are converted to numeric representations via label encoding.
- **Scaling:** Numerical attributes are scaled using Min-Max normalization to bring them to a uniform scale.
- **Splitting:** The dataset is divided into training and testing subsets for model validation.

C. *3) Model Building*

Once the data is preprocessed, neural network models (ANN or CNN) are constructed. These models consist of multiple layers, activation functions, and optimization algorithms tai- lored to classify patients as CKD or not.

D. *4) Model Training*

The training dataset is used to fit the model. Weights and biases are updated using the Adam optimizer to minimize binary cross-entropy loss. Early stopping is used to avoid overfitting by halting training when validation loss ceases to improve.

E. *5) Model Testing and Evaluation*

The trained model is then validated on the reserved test dataset. Metrics such as accuracy, precision, recall, F1-score, and confusion matrix are computed to evaluate performance and generalization capability.

F. *6) Real-Time Prediction*

In deployment, the system accepts real-time user inputs via the frontend. This data is passed through the same preprocess- ing pipeline and then fed into the trained model to obtain a binary prediction (CKD or Not CKD) along with a confidence score.

G. *7) Output and Feedback*

The prediction results are displayed to the user. Addi- tionally, system logs are updated with prediction history for auditing and continuous monitoring.

Fig. 1. Data Flow Diagram of CKD Prediction System

This structured data flow ensures consistency between training and deployment environments and supports future integration with hospital systems or electronic health records.

VI. Results and Discussion

The performance of both the Artificial Neural Network (ANN) and the Convolutional Neural Network (CNN) models was evaluated using key classification metrics including accu- racy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the models' capabilities to accurately detect the presence or absence of Chronic Kidney Disease (CKD) based on clinical attributes. The evaluation was conducted on a holdout test set, and the results reveal significant insights into the effectiveness of deep learning approaches in medical diagnosis.

In terms of accuracy, the ANN model achieved a high score of 99%, indicating that it correctly classified nearly all patient records. The CNN model, however, achieved a perfect accuracy score of 100%, demonstrating its superior ability to generalize and correctly label instances from previously unseen data. Precision, which measures the proportion of true positive predictions among all positive predictions, was slightly lower for the ANN at 97%. This suggests that while the ANN was highly effective, it made a few false positive predictions. In contrast, the CNN achieved a precision score of 100%, indicating that it did not produce any false positives and all positive predictions were correct.

Both models performed equally well in terms of recall, with each achieving a perfect score of 100%. Recall quantifies the ability of the model to identify all actual positive cases, and this result implies that neither model missed any CKD-positive instances in the test set. The F1-score, which is the harmonic mean of precision and recall, was recorded at 98% for the ANN and 100% for the CNN. The slightly lower F1-score for the ANN is due to its reduced precision, despite perfect recall.

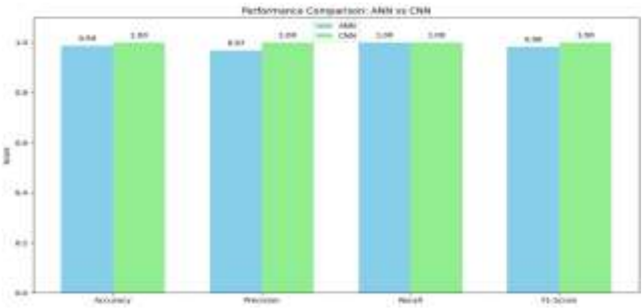

Fig. 2. Comparision of ANN and CNN

These results were visualized in a comparative bar chart, which clearly illustrates the superior performance of the CNN model across all four evaluation metrics. The ANN still demonstrated exceptional performance and proves to be a viable model, particularly for structured tabular data where computational simplicity and speed are desired. However, the CNN model consistently matched or exceeded the ANN in every evaluation criterion, likely due to its ability to detect complex local interactions between features after reshaping them into a spatial format.

Overall, the discussion suggests that while both models are highly accurate and suitable for CKD prediction, the CNN offers slightly better reliability and robustness. These results justify the use of CNNs beyond their traditional domain of image processing and highlight their utility in medical diagnostics involving structured clinical datasets.

VII. References

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E. *Chronic Kidney Disease Prediction using Machine Learning Models(2020), Authors:Revathy Ramesh*