Design and analysis of a novel hybrid approach for the prediction and diagnosis of CKD by using deep learning and Data mining

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Abstract:
Kidney diseases are very common now days, due to the lifestyle change. This is considered as very crucial because any person can only survive maximum 18 days if his/her both kidneys failed. So it is a challenge for clinicians to save the life of patients, that's why the researchers in medical field continuously try to invent new methods to get rid of early detection, calculation and early cure of this CKD. The branch of data mining i.e. ML and DL provide better approaches to predict the image sorting of this disease datasets. This paper shows a hybrid data mining and deep learning approach for prediction of CKD and CRD.

Keywords: CKD, DP, Data Mining, Image classification.

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I. Introduction

Data mining is very significant in the medical field, particularly in the context of predicting and extracting useful information from large and complex healthcare datasets. Data mining is important in early diagnosis for diseases such as kidney cancer and the need for intelligent diagnostic tools to aid healthcare professionals in improving patient health management. The article highlights that data mining techniques, specifically machine learning and deep learning, can be utilized to create intelligent models for early prediction of kidney diseases. Accurately predicting CKD with reduced time complexity remains a challenge when employing these DM and DL algorithms on clinical data related to CKD. Researchers face limitations in terms of accuracy and efficiency when dealing with the complexity and size of CKD clinical datasets, while these classifiers have been explored for CKD diagnosis. The discussed research likely aims to address these challenges by introducing a novel hybrid deep learning mining mechanism, combining the principles of convolutional neural networks (CNNs) and an ensemble with an optimized extreme learning classifier. By doing so, we aim to increase the classification accurateness and decrease the interval intricacy associated with predicting CKD. Overall, the article acknowledges the existing exploration of various classifiers for CKD prediction but highlights the need for more accurate and efficient approaches due to the complexities of CKD clinical data.

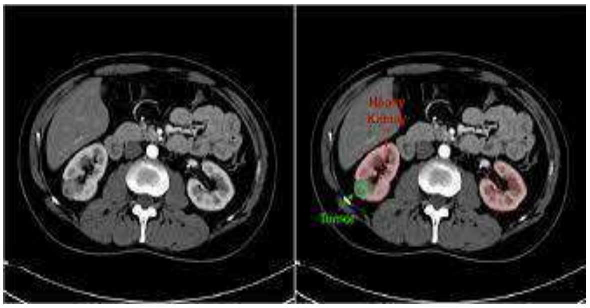

Figure1. Abnormalities in Kidney CT scan Images

The discussed hybrid deep learning mechanism aims to tackle these challenges and provide better prediction results. The discussed research introduces a novel intelligent model that combines deep learning and ML concepts for the primary level prediction and identification of kidney infections. The model utilizes a Hybrid Saliency Convolutional Neural Network to extract saliency segmented Convolutional features. These features are then fed into Ensembled Boosted Extreme Learning Machines (EBELM) for improved performance. The research focuses on CT kidney image datasets and aims to provide an automatic system for physicians to track and predict the growth of kidney cancers, ultimately aiding in diagnosis and treatment. The main contributions of this research work can be concise as below:

1. Design a hybrid deep Convolutional neural network for predicting and diagnosing chronic kidney diseases.

2. Evaluating the discussed architecture using CT image datasets, showcasing its high speed, reduced complexity, and high accuracy.

Overall, the article emphasizes the potential of data mining techniques, particularly deep learning and machine learning, in the early prediction and diagnosis of kidney diseases, thereby enabling more effective healthcare analytics and decision-making processes.

II. RELATED WORKS

V. Kunwar et.al anticipated and analyzed the chronic Kidney Disease utilizing information mining classifiers: ANN and Naive Bayes. Exhibitions of these calculations are thought about utilizing Rapid excavator device. The acquired outcomes showed that Naïve Bayes is the most precise classifier with 100% exactness when contrasted with ANN having 72.73% exactness. In this exploration study, a portion of the variables considered were age, diabetes, pulse, RBC tally and so forth The work can be reached out by considering different boundaries like food type, working climate, day to day environments, accessibility of clean water, ecological variables and so forth for kidney illness identification. Further investigations can be led utilizing different classifiers like Fuzzy rationale, KNN. Principle benefit of this edge work incorporate high figure execution when handling enormous information, strength and flexibility to differing data sources and yields. Every one of these empowers its utilization in clinical dynamic. In any case, this structure need to focus boundaries, for example, food type, working climate, everyday environments, accessibility of clean water, natural components and soon[13].

L. Jena et.al objective is to anticipate constant kidney infection. We have utilized two calculations for example Credulous Bayes and Multilayer Perceptron for tests. These calculations are executed utilizing WEKA AI instrument to examine exactness which is gotten in the wake of running these calculations in the yield window. Subsequent to running these calculations the yields are analyzed based on exactness accomplished. These calculations have been contrasted with grouping exactness with one another based on accurately characterized occurrences, mean total blunder, Kappa measurements and RMSE metric. The outcomes show that MLP classifier beats Naïve Bayes classifier in all area concerning the boundaries indicated. It is reasoned that MLP classifier is the best expectation calculation for ongoing kidney illness determination. In future we will think about some more characterization. In any case, this strategy enormous memory for the quick expectation[14]

B. J. Sahana et.al achieves improved classification performance compared to existing techniques, indicating its effectiveness in identifying CKD cases accurately. Furthermore, the D-ACO algorithm demonstrates high classification performance using only a reduced set of relevant features, leading to optimal performance measures. This suggests that the discussed algorithm can achieve accurate classification results while minimizing the number of features required for prediction. In summary, the study concludes that the D-ACO algorithm is a suitable classifier for identifying CKD cases. It offers enhanced classification performance compared to existing methods and achieves optimal performance measures by utilizing a reduced set of relevant features. This system creates high grouping execution and accomplish ideal execution estimations[16].

P. Nisarga et.al predominantly revolves around recognizing risky sicknesses like CKD by grouping component Naïve Bayes. The stage forecast depends on the Glomerular Filtration Rate. The idea can be executed for a facility or medical clinic for investigating the CKD patient's information. The idea can be executed as an online wellbeing local area sys-tem where patients can assemble CKD and stages data. The idea can be carried out for an examination office for investigating the connection among CKD and its various stages. This casing work utilizes the restricted re-sources to upgrade the patient organization. In any case,decline in various highlights doesn't guarantee successful arrangement execution[17].

M. Thiyagaraj et.al means to examine the different information mining methods in clinical space and a portion of the calculations used to foresee kidney illnesses in the end. From the above overview, it is demonstrated that outcomes may change for various phases of kidney sickness finding dependent on the instruments and strategies utilized. Information mining gives better outcomes in illness finding when proper methods utilized. Hence, information mining is the critical field for medical services expectation. By utilizing the information mining systems, Patients misuse better and more noteworthy reasonable medical care administrations. Be that as it may, It Involves protection issues and security issues [20].

In the study conducted by E.M Senan et al., the focus is on utilizing AI techniques for early diagnosis of chronic kidney disease (CKD) to assist specialists in analyzing preventive measures. The study utilizes a dataset collected from 400 patients, consisting of 24 features. Missing numerical and nominal values are replaced using mean and mode statistical analysis techniques. Recursive Feature Elimination (RFE) is applied to select the most important features. Four classification algorithms, namely support vector machine (SVM), k-nearest neighbors (KNN), decision tree, and random forest, are applied in the study. All the classification algorithms achieve promising performance, with the random forest algorithm outperforming the others by achieving 100% accuracy, precision, recall, and F1-score for all actions. CKD is a serious and dangerous disease with high rates of morbidity and mortality. Therefore, the use of artificial intelligence techniques for early detection is crucial. These methods support specialists and physicians in early diagnosis to prevent kidney failure. While this method is supportive of larger datasets, it does have a high training time.

III. Discussed methodology

A. IMAGE DATA PREPROCESSING Data preprocessing techniques are applied to the kidney CT scan images to eliminate noisy and low-quality pixels that could hinder the detection of chronic kidney cancers. Pixel-intensive techniques are used to remove inconsistent and noisy pixels from the original images. Additionally, image histogram methods are employed to enhance the image quality, as they work effectively on various types of images. The preprocessed CT kidney images are presented in Figure 3.

B. SALIENCY SEGMENTATION Segmentation involves dividing images into different regions based on varying textures and pixels. Various methods have been developed for image segmentation. In this work, a novel methodology called visual saliency maps descriptors is introduced. This methodology decomposes the images into compact and heterogeneous elements, eliminating unnecessary components through subtraction.

C. FEATURE EXTRACTION USING CONVOLUTIONAL NEURAL NETWORK In this research, the segmented images are inputted into a CNN for effective feature extraction. CNN is a biologically inspired advancement of the MLP and finds extensive applications in image classification, object detection, image clustering, optical character recognition, natural language processing, and even sound analysis when represented as spectrograms. CNNs have also been applied to text analysis and graph data using graph convolutional networks. The superior performance of CNNs compared to other algorithms has made them successful in various fields.

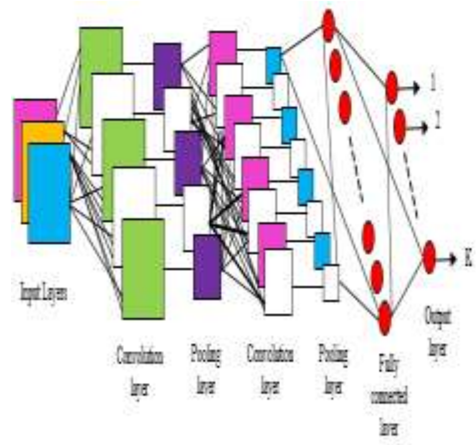

Figure 2: CKD dataset Image Intensification

Figure 2 illustrates the working of a CNN in feature identification. In a CNN, features are detected using channels or filters. Each channel is a grid of weights that are trained to detect specific features in the input data. The purpose of these channels is to perform the convolution operation, which involves element-wise multiplication and summation between the weights and the input grids. During CNN training, redundancy in the input features is reduced to optimize memory consumption. One common technique used for this purpose is max pooling. In max pooling, a window or kernel scans the input data, and the maximum value within the window is selected and pooled into an output grid. This process helps to retain the most relevant and significant features while reducing the dimensionality of the data. The efficiency of feature extraction in CNNs is achieved by combining multiple convolutional layers and max pooling operations. The input data is processed through these deep layers, with each layer learning increasingly complex and abstract features. This hierarchical feature extraction allows the CNN to capture intricate patterns and representations in the data. The final output of the convolutional layers is a set of feature maps, which are essentially grids representing the learned features. These feature maps are then converted into a feature vector by passing them through a Multi-Layer Perceptron (MLP) or fully-connected layer. The MLP performs higher-level reasoning and decision-making based on the extracted features, enabling the model to make predictions or classifications based on the learned representations. Overall, CNNs leverage channels, convolutional layers, max pooling, and fully-connected layers to identify and extract meaningful features from the input data, enabling them to perform complex tasks such as image recognition, object detection, and classification.

D. MODEL TRAINING Once the features are extracted, they are used to train the networks. In the discussed architecture, traditional training networks are replaced with feed-forward networks based on the principles of Extreme Learning Machines (ELM). Extreme Learning Machines are a category of machine learning algorithms.

E. DRAWBACKS OF ELM One drawback of ELM is that its auto-tuning properties can lead to the creation of redundant nodes, which can impact the performance of the training network. To address this drawback, the discussed framework incorporates the Deer Hunting (DH) algorithm to obtain the hyperparameters of ELM for optimal performance. The working mechanism of the Deer Hunting algorithm is explained in the preceding section.

F. DEER HUNTING OPTIMIZATION In this approach, an optimum point is chosen for hunting a deer, and the behavior of the deer is studied. Hunting is a complex process for attackers due to several characteristics. The visual power of a deer is highly effective compared to human beings, but it suffers from color deficiency, where red and green colors are insignificant to a deer. A deer, also known as a buck, is capable of detecting even the slightest movement, and studies have shown that a white-tailed deer has a peripheral vision ranging from

250° to 270°. This allows a buck to anticipate the actions of a hunter within the defined range. The sensitivity of a white-tailed deer in sensing changes in the environment is superior to that of human beings. Additionally, the olfactory sensors of bucks are highly effective compared to humans.

IV. DHO BASED ELM TRAINING PROCESS

Advantage of integrating DH algorithm in ELM increases the global minima in search path which is then more efficient than the existing optimization algorithms. The discussed framework uses accuracy as the function.

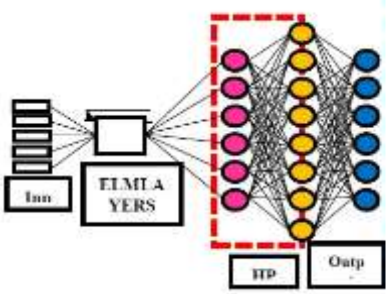

Figure3. DH-ELM training network used for the better classification process.

Figure 3 shows the DH-ELM training network. The hyper parameters such as input bias weights, hidden layers, epochs and learning rates are considered to be initial parameters of the deer hunt optimization. These parameters are iterated until it meets the fitness function which is given in Equation 1. The iteration continues until the accuracy of the discussed algorithm equals to its fitness function. The mathematical equation for the fitness function is given:

$$\text{Fitness Function} > \text{Min(Accuracy)} \quad \ldots(1)$$

V. COMPARATIVE ANALYSIS OF PERFORMANCES FOR THE DIFFERENT LEARNING MODELS

we have compared the performance of the discussed algorithm with the other learning based classification approaches such as deep convolutional neural network(DCNN), SVM, RF, adaptive hybrid convolutional neural network (AHCNN),Naïve Bayes(NB), J48 and MLELM.

Table 1. Relative exploration of performances for the various learning approaches

Performance Metrics (%)					
Algorithm	Accuracy	Precision	Recall	Specificity	F1-Score
DCNN	94	93.5	92.5	93	93.4
SVM	89	88.5	88	87.4	87
RF	83	84.2	84.4	83.7	84.2
AHCNN	94	93.5	94.5	94	94.2
NB	78.4	76.4	77.5	74.6	75
J48	75.5	75	75.3	75.4	75.3
MLELM	82.78	82.6	80.4	81	80.7
PROPOSEDMODEL	99.2	99.4	99.38	99.6	99.7

furthermore, to test the stability of the discussed model, we have used different dropouts for the datasets and analyzed the performance metrics which is shown in Figure. It is found that the discussed model has exhibited the optimal performance for the "n" number of datasets. Figure 4 shows the measures of performance with the different dropouts.

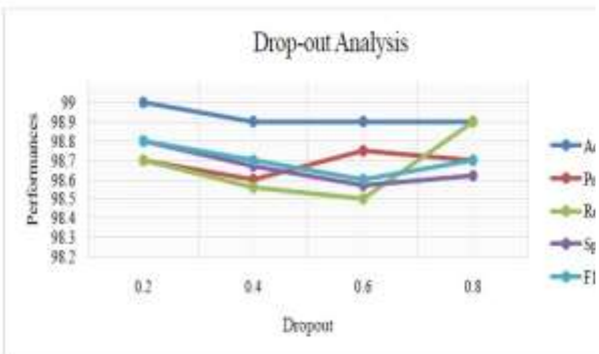

Figure 4. Drop-out Performance

From the Figure 4, it is evident that performance of the discussed model remains stable even the datasets increases for the different drop-out mechanism. The successful integrationof optimized Extreme learning machines along with the deep convolutional features extractions has proved to be vital in kidney disorders detections even under different dropout ratios.

VI. Conclusion:

This paper presented an approach for the detection and prediction CKD at early level. The discussed method employed saliency maps and deep convolutional layers for accurate segmentation and feature extraction. These features were then utilized to train the network for improved classification of cancer cells. The architecture also incorporated Extreme Learning Layers, which contributed to accurate image classification while reducing computational complexity. The utilization of boosted extreme learning machines proved to be efficient in the detection of kidney diseases, particularly cancer cells. Not only did the discussed approach demonstrate superior performance compared to existing methods, but it also exhibited reduced computational complexity. These findings highlight the potential of the discussed approach for accurate and efficient detection and prediction of cancer cells using CT scan kidney images.

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