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RESEARCH ARTICLE

CKD-DBN: CHRONIC KIDNEY DISEASE DETECTION USING DEEP LEARNING BASED DEEP BELIEF NETWORK

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Abstract – chronic kidney disease (CKD) is a long-term condition characterized by the gradual loss of kidney function over time. The kidneys are essential organs that filter waste and extra fluid from the blood so that it can be expelled as urine. Early detection is crucial for managing progression and associated complications. However, manual detection of kidney disease is time-consuming and challenging task in the current setup. In this work, a novel deep learning-based CKD-DBN model has been proposed for identifying CKD in its early stages. Initially, the CT images are gathered from the publicly available dataset and these gathered images are pre-processed using median filter to eliminate noise while preserving edges in the image. The pre-processed images are fed into the GhostNet for feature extraction that extracting significant features from the input images. Finally Deep Belief Network (DBN) classifies the images into Normal or CKD based on these features. The proposed CKD-DBN model is evaluated based on its f1 score, recall, specificity, precision and accuracy. The classification accuracy of 98.82% for the proposed are highly reliable for public available dataset. The proposed CKD-DBN model achieves the overall accuracy by 1.84%, 0.82% and 2.85% comparing to the existing method such as ALO, DNN and RNN.

Keywords *– chronic kidney disease, deep learning, median filter, GhostNet, deep belief network.*

1. INTRODUCTION

The kidneys are a vital organ that the body needs to function normally. They keep the body's fluid equilibrium, filter blood, and remove waste through urine. CKD results from a renal dysfunction [1]. Kidney damage brought on by an improper blood filter is known as CKD. Put another way, a person with CKD experiences a buildup of waste products in their body, which results in symptoms like fever, rash, diarrhea, vomiting, back pain, and nosebleeds. Damage that builds up gradually over time will have an impact on the entire body and cause a variety of diseases to arise [2]. Kidney disease can result from a number of conditions, such as glomerulonephritis, hemolytic uremic syndrome, uncommon blood disorders, kidney cysts, nephrolithiasis, kidney stones, and blood clots [3]. In other words, a collection of waste products in the body causes signs including fever, rash, diarrhea, vomiting, back pain, and nosebleeds in those with CKD [4].

Blood pressure and blood sugar management are the greatest ways to avoid CKD. CKD can also be prevented by eating a balanced diet, exercising frequently, maintaining a healthy weight and receiving routine exams and tests. In order to avoid major consequences, CKD should be detected and treated early [5]. A recently developed method of radiomics-based machine learning (ML) and DL procedures that extract measurable analytic material from MI has enabled the diagnosis and prognosis of CKD [6]. Limiting health problems for the patient and stopping the disease from spreading can be achieved by keeping an eye on risk factors and identifying the illness early. GFR, or glomerular filtration rate, is a highly accurate indicator of kidney health. The GFR measurement of a patient reveals their degree of renal function. As kidney disease worsens, its value begins to decline. It is designed with the patient's blood count, age, gender, race, and other relevant parameters in mind [7]. The key contributions of this work are summarized as,

- The primary purpose of this research is to designed a novel DL-based CKD-DBN model has been proposed for classifying normal and CKD.
- Initially, the CT images are gathered from the publicly available dataset and these gathered images

are pre-processed using median filter to reduce noise in the image.

- The pre-processed image is fed into the GhostNet for feature extraction that extracting significant features from the image.
- Finally Deep Belief Network (DBN) classifies the images into Normal or CKD based on these features.
- The efficiency of the proposed CKD-DBN model was assessed based on the criteria includes f1 score, specificity, precision, accuracy and recall.

The structure of the paper is organised as follows, section-2 briefly explains the literature survey, the proposed GhostNet was explained in section-3, The performance results and their comparison analysis were provided in section-4 and section-5 encloses with conclusion and future work.

2. LITERATURE SURVEY

In recent years, several researches have investigated for the CKD with DL and ML methods. The section that follows provides a review of some current research papers.

In 2022, Singh, V., et al., [8] suggested a DL model to detect and predict CKD early. With 100% precision, the four classifiers such as naive bayes, support vector machine, random forest, K-nearest neighbour, and logistic regression were outperformed by the suggested deep neural model. The suggested approach may be useful to nephrologists in diagnosing CKD.

In 2021, Akter, S., et al., [9] suggested seven cutting-edge DL techniques for CKD classification and prediction. Five distinct methodologies were used to extract and evaluate characteristics from pre-processed CKD datasets in order to apply the suggested algorithms, which were based on artificial intelligence. Algorithms like Simple RNN, ANN, and MLP offered great accuracy and a strong prediction ratio in addition to shorter processing times when it came to classifying CKD.

In 2023, Kumar, K., et al., [10] suggested a DL model for renal illness detection and prediction that integrates a fuzzy deep neural network. The suggested model outperforms current techniques with an accuracy of 99.23%, according to the results. Furthermore, research in the future can prove the accuracy of detecting chronic disease without the need for medical professionals.

In 2019, Kriplani, H., et al., [11] presented a system for predicting CKD based on DL. The suggested method is based on a DL, which has a 97% accuracy rate in forecasting the existence or non-appearance of CKD. The typical outperforms other existing techniques. It is protected against overfitting by employing the cross-validation methodology.

In 2018, Shankar, K., et al., [12] suggested a method for classifying CKD using a DL classifier. Using the ant lion optimization (ALO) strategy, the suggested method chooses relevant features from the renal data in order to select the best characteristics for the classification procedure. When related to current data mining classifiers, classification metrics including accuracy, sensitivity, specificity, and precision produced the best results, with 98% of DNN having the highest accuracy.

In 2020, Iliyas, I.I., et al., [13] proposed a DL method for CKD estimate. The patients' presence or absence of CKD was predicted using the DNN model. The model yielded a 98% accuracy rate. Additionally, we determined and emphasized the features' significance in order to produce a ranking of the features that are utilized in the CKD prediction.

In 2024, Saif, D., et al., [14] suggested a CKD prediction system that uses DL and deep ensemble learning methods to forecast the incidence of CKD ended a specific time frame. The top three models and optimizers are combined to create the ensemble model. The approach produces far better accuracy than earlier research, opening the door to early diagnosis and better patient outcomes.

Based on the above literature survey, existing techniques was developed using various DL and ML approaches to the classification of CKD. However, these methods are fails to provide the high reliability rate and the process of identifying kidney disease need more time. To address this challenge, a novel DL-based CKD-DBN model has been proposed for more effective identification of kidney from images.

3. PROPOSED METHODOLOGY

In this section, a novel DL-based CKD-DBN model has been proposed for identifying CKD in its early stages. The CT scans are collected from the publicly accessible dataset and they are pre-processed by a median filter to reduce image noise. The pre-processed image is fed into the GhostNet for feature extraction that extracting significant features from the image. Finally Deep Belief Network (DBN) classifies the images into Normal or CKD based on these features. Figure 1 shows the suggested CKD-DBN methodology.

3.1 Dataset description

The CKD data was gathered from the UCI Repository. In the 400 patient records that make up the data collection, certain values are absent. The prognosis of CKD is based on 24 clinical features, one of which is a class attribute that is derived from the prediction of the patient's existence of chronic renal failure. CKD and not CKD are the two types of values in the anticipated feature analytical. 250 values (62.5%) from the CKD class and 150 values (37.5%) from the not CKD class are included in the data set.

3.2 Pre-processing

The median filter is applied as a pre-processing step to the input CT scans in order to minimize image noise. A common technique for image denoising is the median filter, which replaces the targeted pixel point with the neighbourhood area's median of each pixel value. This helps to remove isolated noise from images.

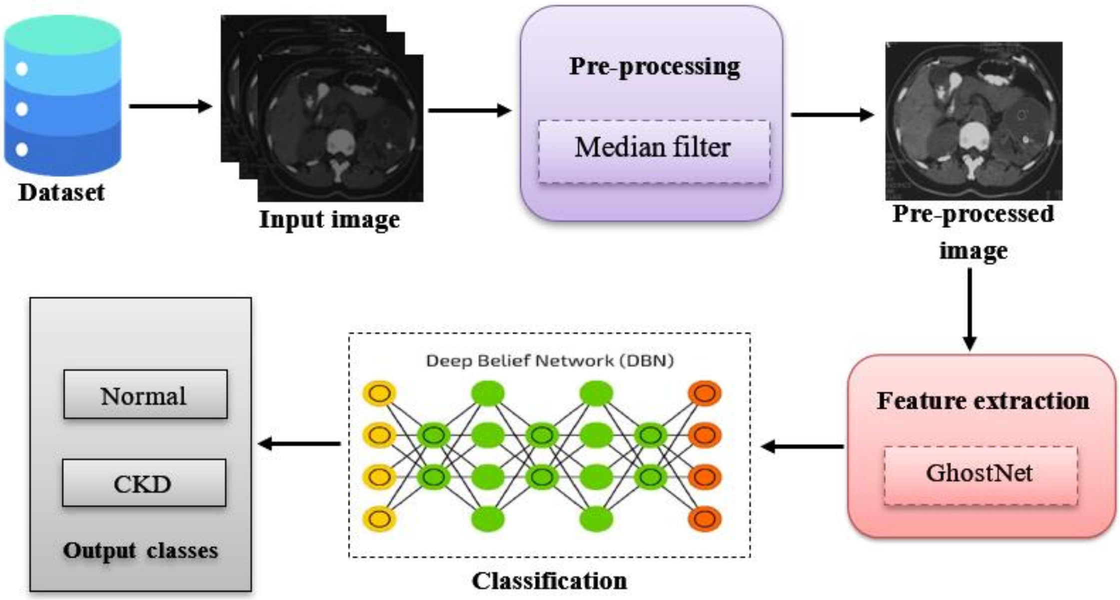

Figure 1: The proposed CKD-DBN methodology

In addition to preserving image detail and marginal information, this might make the neighbourhood pixel values more acceptable. After median filtering, the value of the image pixel f (x, y) at the organizes (x, y) can be stated as follows:

$$F\ (x,y) = median(l(x+i,y+j))fx,y = medianlx + i,y+j \quad (1)$$

where the neighbourhood pixel values are expressed as l (x + i, y + j) with respect to the centered pixel point (x, y) and the median () function denotes the median selection of the neighbourhood pixel values. During the denoising process, the image can be filtered using a two-dimensional 3 × 3 window. By comparing its sizes to the pixel values that lie inside a particular series, a median can be designated as the new center pixel.

3.3 Feature extraction

The pre-processed images are fed into the GhostNet for feature extraction that extracting significant features from the input images. Numerous convolutions are frequently used in deep convolutional neural networks, which leads to extremely high computing costs. Considering that standard CNNs compute intermediate feature maps with a lot of redundancy to cut down on the resources needed to create them convolution filters. The following is a practical definition of how a subjective convolutional layer generates n feature maps: Considering that X ∈ $R^{(c\times h\times w)}$, where c is the number of input channels and h and w are the input data's height and breadth.

$$Y = X * f + b \quad (2)$$

where f ∈ $R^{c\times k\times k\times n}$represents the convolution filters in this layer, Y∈$R^{h'\times w'\times n}$ is the output feature map with n channels and ∗ is the convolution procedure. Furthermore, k ×k is the kernel size of convolution filters f, $h'$and $w'$are the height and width of the output data. Since the number of filters (n) and the channel number (c) are typically quite big, the necessary number of FLOPs for this convolution technique can be computed as n. This figure is often as huge as hundreds of thousands.

According to Equation 2, the number of parameters (in f and b) that require improvement, directly influenced by the input and output feature maps sizes. Convolutional layer output feature maps frequently have a lot of redundancy, and some of them may be comparable to one another. Generating these redundant feature maps with a lot of FLOPs and parameters one by one is not necessary. Assume that a few intrinsic feature maps produced by a few simple operations are the ghosts of the output feature maps. Often smaller in size, these intrinsic feature maps are created using standard convolution filters. Specifically, a primary convolution is used to generate m inherent feature maps $Y' \in R^{h'\times w'\times m}$.

$$Y' = X * f' \quad (3)$$

In this case, m ≤ n, $f' \in R^{c\times k\times k\times m}$ describes the filters that are utilized; for simplicity, the bias term is omitted. In order to maintain uniformity in the output feature maps' spatial dimensions, the hyper-parameters employed in the traditional convolution (Equation 4) are filter size, stride, and padding. Applying a number of low-cost operations to each intrinsic feature in Y' will produce s ghost features in accordance with the function below, which will help achieve the desired n feature mappings.

$$y_{ij} = \Phi_{i,j}(y_i'), \qquad \forall i = 1, \dots\dots, m, \quad j = 1, \dots., s, \quad (4)$$

The C-Ghost module's output data is n = m. s feature mappings Y = [$y_{11}, y_{12}, \dots\dots\ y_{ms}$], which we may acquire by using equation. Keep in mind that each channel that the low-cost operations Φ work on has a computational cost far lower than that of a standard convolution. In actual use, a C-Ghost element may contain a variety of inexpensive operations, such 3×3 and 5×5 linear kernels, which will be investigated in the section on experiments.

3.4 Classification

Finally Deep Belief Network (DBN) classifies the images into Normal or CKD based on these features. A special kind of DL model composed of several layers of Restricted Boltzmann Machines (RBMs) is called a DBN. Deep, hierarchical designs are created in DBNs by stacking RBMs on top of one another. The DBN framework correlates the quantity of data characteristics with the no. of input levels and the quantity of output layers with the variety of categories. The data input distribution is characterized by using hidden variables in a statistical synthesis model with deep designing DBN. Figure 2 shows the DBN architecture.

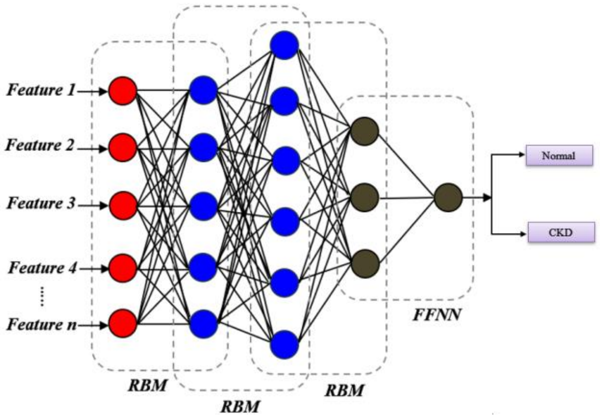

Figure 2. Deep Belief Network architecture

The DBN was designed in order to create a two-step learning process. The initial phase was greedy layer-wise training for each RBM. At this stage, each RBM learned to identify the basic patterns in the data, disregarding the network's overall complexity. The next stage involved making systemic improvements to reduce the modification between the original data and the recreated data produced by the DBN. It was definitely worth the effort and a significant amount of processing power to complete this task.

It can be used to compute probability ranges across concealing and evident items provided (u, l) stands for the concealed and apparent levels, X for the partition function, and Z for the energy measure.

$$D(u,l) = \frac{1}{Y}\exp\left(-A(u,l)\right) \tag{5}$$

The principal feature (U) of DBN is its weight, which is determined by an RBM and learned p $(w|f,U)$. The previous mean for bearers who are concealed $q(f|w)$. Equation (6) expresses the pace at which an apparent gradient is produced.

$$P(w) = \sum_f (p\left(\frac{f}{U}\right) p\left(\frac{w}{f}, U\right)) \tag{6}$$

$sum(z_d)$ the vector used to connect the DBN's total hidden layers, should look like this:

$$sum(z_d) = \sum_{cj=1}^{m} num(fdc_j) \tag{7}$$

Using the weight and bias of the images to display the output of the hidden or invisible layer in equation (9).

$$A^d = \left[\sum_{m=1}^{l} Z_{md}^{G^t} * p_m\right] A_d \forall p_m = e_m^2 \tag{8}$$

The output of the RBM layer for the multilayered classification process is denoted by p_m where A^d stands for the hidden layer bias of the data.

4. RESULTS AND DISCUSSION

The suggested CKD-DBN is assessed by different measures includes f1 score, precision, recall, specificity and accuracy. The benchmark includes the total accuracy rate, which is explicitly specified and evaluated, as well as the proposed model's performance. The proposed network is also evaluated with classic DL models.

4.1 Performance analysis

A proposed CKD-DBN model can be assessed based on recall, specificity, precision, accuracy and f1 score.

$$Specificity = \frac{T_{neg}}{T_{neg}+F_{pos}} \tag{9}$$

$$Precision = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{10}$$

$$Recall = \frac{T_{pos}}{T_{pos}+F_{neg}} \tag{11}$$

$$Accuracy = \frac{T_{pos}+T_{neg}}{Total\ no.of\ samples} \tag{12}$$

$$F1\ score = 2\left(\frac{Precision+Recall}{Precision+Recall}\right) \tag{13}$$

Where T_{neg} and T_{pos} specifies true negatives and true positives of the sample images, F_{neg} and F_{pos} specifies false negatives and false positives of the sample images.

Table 1. Performance assessment of the proposed CKD-DBN model

Classes	Accuracy	Specificity	Precision	Recall	F1 score
Normal	99.41	98.83	95.73	96.63	95.03
CKD	98.23	97.05	96.22	94.02	93.87

Table 1 displays the classification performance obtained by proposed CKD-DBN model for classifying the LC. Recall, f1 score, specificity, accuracy and precision are metrics that determine performance. A total accuracy of 98.82% is achieved by the suggested CKD-DBN model using the dataset. The proposed CKD-DBN model also achieves 97.94%, 95.97%, 95.32%, and 94.45% overall specificity, recall, precision and f1 score. Figure 3 provides a graphic representation of the CKD-DBN model performance assessment.

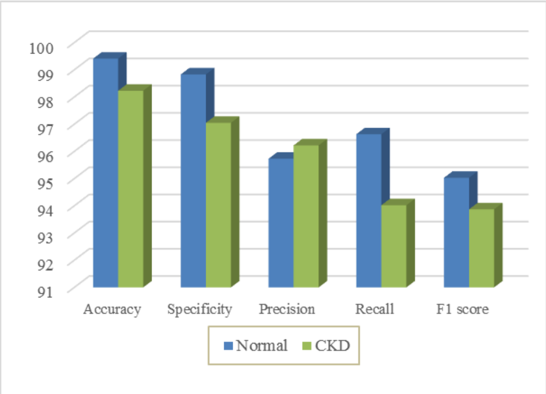

Figure 3. Graphical representation of performance analysis

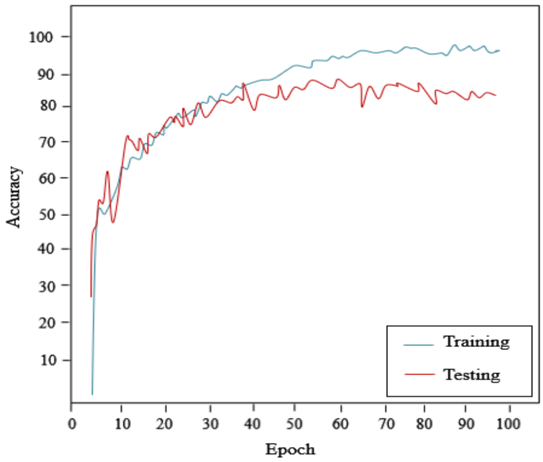

Figure 4. Training and testing accuracy curve of GhostNet

Figure 4 shows epochs on the x and y axes, along with a comparison of testing and training accuracy. Figure 5 indicates a loss curve plotted against epochs, which shows that the loss decreases with rising epochs. The proposed procedure yields an accurate result with a reasonably low loss of 1.18%. With a low percentage of errors, the proposed CKD-DBN achieved 98.82% training and testing accuracy based on the number of epochs.

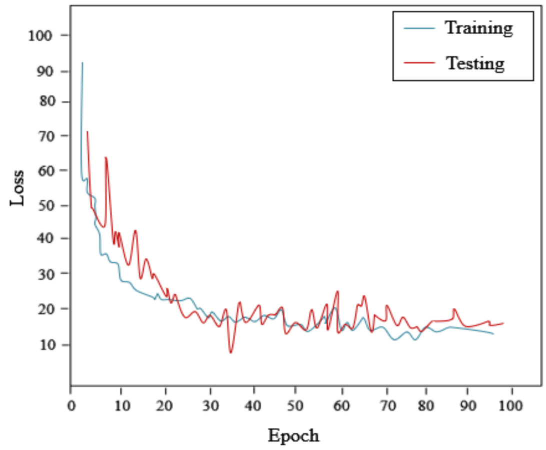

Figure 5. Training and testing loss curve of GhostNet

4.2 Comparative analysis

The efficiency of DL network was determined in order to verify that the proposed CKD-DBN generates results with a high level of accuracy. The proposed GhostNet and four classifiers AlexNet, RegNet-50, DenseNet and MobileNet were compared. A variety of measures were used to evaluate each DL techniques performance including recall, f1 score, accuracy, precision and specificity.

Table 2. Comparison of convolutional networks with GhostNet

Networks	Accuracy	Specificity	Precision	Recall	F1 score
AlexNet	93.65	90.04	94.23	92.21	90.25
ResNet-50	95.28	94.58	91.04	95.05	91.48
DenseNet	94.45	96.24	92.45	94.28	94.24
MobileNet	97.07	92.56	95.27	90.75	93.75
GhostNet	98.82	97.94	95.97	95.32	94.45

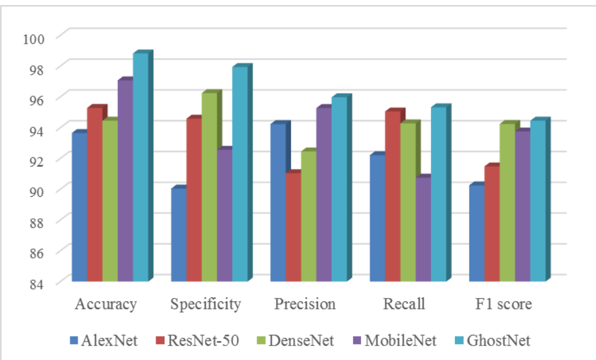

Figure 6. A graphic representation of performance analysis for GhostNet

To compare several DL networks based on performance measures and determine an appropriate percentage of classification accuracy, Table 2 was examined. In contrast to the proposed CKD-DBN model, the conventional networks did not perform as well. The suggested GhostNet outperforms AlexNet, ResNet-50, DenseNet and MobileNet by 5.23%, 3.58%, 4.42% and 1.77% respectively, in terms of overall accuracy range. Figure 6 shows a graphic representation of the GhostNet comparative evaluation.

Table 3. Comparison of existing method versus proposed CKD-DBN method

Authors	Methods	Accuracy
Kriplani, H., et al., (2019) [12]	ALO	97%
Shankar, K., et al., (2018) [13]	DNN	98%
Akter, S., et al., (2021) [9]	RNN	96%
proposed	GhostNet	98.82%

According to Table 3 the contrast of the suggested and the existing methods are demonstrated. The proposed CKD-DBN model achieves the overall accuracy by 1.84%, 0.82% and 2.85% comparing to the existing method such as ALO, DNN and RNN. However, the proposed CKD-DBN model produced better fallouts than the previous methods. As a result, the proposed model's attains high prediction rate for classifying the CKD.

5. CONCLUSION

In this research, a novel DL-based CKD-DBN model was proposed for detecting CKD. Initially, the CT images are collected from the publicly available dataset and these gathered images are pre-processed by median filter to decrease noise in the image. The pre-processed images are fed into the GhostNet for feature extraction that extracting significant features from the image. Finally, DBN classifies the images into Normal or CKD based on these features. The proposed CKD-DBN model is evaluated based on its f1 score, specificity, precision, recall and accuracy. The proposed GhostNet outperforms AlexNet, ResNet-50, DenseNet and MobileNet by 5.23%, 3.58%, 4.42% and 1.77% respectively, in terms of overall accuracy range. The classification accuracy of 98.82% for the proposed are highly reliable for public available dataset. The proposed CKD-DBN model achieves the overall accuracy by 1.84%, 0.82% and 2.85% comparing to the existing method such as ALO, DNN and RNN. The performance of our proposed approach is slightly low due to the limited number of datasets, so in future, different data augmentation techniques and advanced optimization algorithms will be utilized to improve the performance of the suggested method.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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