Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks

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***Abstract*—Chronic Kidney Disease (CKD) is a chronic disease that progressively impairs kidney function to the point of wasting filtration, electrolyte imbalance, and blood pressure control. Early and precise prediction becomes necessary for successful disease management. This research demonstrates a new method involving Deep Separable Convolutional Neural Networks (DS-CNNs) in improving CKD prediction. Based on the Chronic Kidney Disease Dataset available at Kaggle, the model employs DS-CNNs combined with optimized techniques of optimization for better predictive accuracy. DS-CNNs utilize depthwise and pointwise convolutions to facilitate effective feature extraction and classification with efficient computation. To enhance model performance, the Learning Rate Warm-Up with Cosine Annealing technique is used to guarantee stable convergence and controlled rate of reduction in the learning rate. This solution remedies the inadequacies of traditional CKD detection solutions that are insensitive to early stages and entail expensive, invasive procedures. At 94.50% accuracy, the new DS-CNN model outcompetes conventional methods, featuring better prediction performance. The results demonstrate the utility of deep learning and optimization in early detection of CKD and introduce a promising tool for enhanced clinical decision-making.**

***Keywords*—Chronic kidney disease; deep separable convolutional neural networks; learning rate warm-up with cosine annealing; predictive accuracy; optimization techniques**

I. INTRODUCTION

CKD presents a significant global health challenge, affecting approximately 850 million people worldwide [1]. The kidneys are two of the most important organs in the human body located on the right and left flanks of the spine and in the abdominal region just below the rib cage They have the function of regulating water and electrolyte balance and maintaining the body's internal pH by filtering out waste products, excess water and toxins from the blood in the form of urine. Also, they maintain the electrolyte concentration, blood pressure, as well as the acid and base balance; synthesize hormones which are involved in calcium regulation and erythropoietin, which is responsible for the production of red blood cells. CKD is defined by persistent and gradual decrease in the kidney's function and the failure a kidney to remove wastes and balance fluids leading to the build-up of potentially toxic substances and swelling [2].

Chronic kidney disease is a global health issue that still poses great diagnostic challenges especially in the Low- and middle-income countries, hence it often presents itself as a huge burden to the affected patients. Here, inadequate resources and capacity of healthcare facilities hamper early detection and treatment, exacerbating the disease's impact CKD requires timely diagnosis and management to delay the worsening condition to stage 5 where patients usually require costly treatments such as dialysis. However, inadequate screening programmes and relevant facilities restrict access to needful treatments in the region. In addition, other sociodemographic factors and poor health funding existing in the society also lead to disparities in management and overall health of individuals with CKD. These difficulties can only require specific actions to enhance the facilities, increase the understanding and accessibility of satisfactory renal care to people [3]. In Stage 1 the kidneys work effectively to perform all their tasks as they should. At stage 2, common investigations show a slight reduction of function where a body is sometimes able to filter small wastes. Kidneys are severely damaged and, at Stage 3, the patient experiences clearCut impairment of waste removal. Stage 4 is characterized by moderate losses but loss of function is not complete in this stage. The last stage is the stage 5 also known as renal failure which means that the kidneys cannot execute their main functions, so dialysis or transplantation of the kidneys is required.

It is interesting to note that, commonly used primary screening for chronic renal disease, serum and urine test often fail to give an early sign of kidney dysfunction. Such tests are unable to reflect small initial differences in the kidney or variations over time and, therefore, give a delayed diagnosis [4]. In addition, extensive information providing methods like kidney biopsies, are not appropriate for routine screening processes because they involve very intensive procedures and potential risks. The mentioned constraints are solved by Machine Learning (ML) approaches [5] and this option seems quite convincing. It is, however, clear that using big and complicated data, ML systems are capable of identifying fine changes in patterns of kidney function, and that earlier work may miss [6]. Since the factors taken to be used in building an ML model include demographic factor, medical history and clinical test results among others, the models can give more precise and hence be better at doing the CKD risk assessment. The mentioned capacity enables the formulation of specific treatment plans for patients depending on certain general profiles. The efficiency of ML algorithms also enables quicker analysis of new patients' information, which is crucial for the initial diagnosis and treatment. These algorithms can quickly adapt to new knowledge and incorporate this new information through changes in the patient's health into the diagnostic process. Additionally, with the help of machine learning algorithms it is possible to predict the probability of the CKD progression in high risk population and estimate the preventative measures required [7]. Such an approach is quite effective in positively impacting the overall prognosis of the patient since issues that could potentially be of serious concern if left unaddressed are likely to have been dealt with in the act. Taken collectively, it could be postulated that ML algorithms are potentially superior to conventional methods of CKD diagnosis, and as such, they are valuable tools in the fight against this prevalent and significant health condition.

As a result, many studies have had to harness other approaches that are at the algorithm level like ensemble learning and cost-sensitive learning rather than data level techniques [7]. Ensemble learning is a revolutionary concept in the arena of ML study and implementation employed to achieve very high accuracy of the classifier through integration of one or more classifiers. Boosting [8] and Bagging [9] are widely used ensemble learning techniques. Therefore, in this study, we develop an AdaBoost classifier that gives higher weight to examples in the minorities, thus improving the prediction of the samples of the minority class and the global classification accuracy [11]. The currently used techniques for CKD diagnosis such as blood tests, urine tests, and even invasive techniques like biopsy have various drawbacks. These methods are usually not very accurate when it comes to determining the early sign of kidney failure and the changes in the kidney function with time, therefore the diagnosis and treatment for the kidney diseases are often delayed. In addition, KUB radiography, ultrasonography and CT scans are expensive and sometimes take a lot of time which limits their use. In spite of the fact that the validity of CKD detection has increased with the help of ML methods which analyze big data and find rather complicated patterns, however, there are the disadvantages of such methods [10]. The issue with the current paradigm of using conventional ML algorithms, however, is an inability to adequately process the data, particularly if CKD cases are vastly in the minority compared to controls represented by non-CKD patients.

Some of the problems are solved by the generic ensemble learning techniques such as AdaBoost that involves using multiple classifiers brought together to enhance the accuracy of the classification process as well as work on imbalanced data set. Nevertheless, they can still encounter difficulties in terms of low computational efficiency for the data with large dimensionality and the complexity of feature interactions. The above-mentioned limitations are inherited from the traditional machine learning frameworks, and can be mitigated with the help of the proposed state-of-the-art deep learning framework, namely Deep Separable Convolutional Neural Networks (DS-CNNs). DS-CNNs gives better accuracy in detecting the changes in the CKD as convolutions lead to the structural difference that improves the working ability of the model and early stage of kidney damage. In addition, this conceptual framework proposes methods for dealing with imbalanced data which enables both the minor and major classes to be dealt with equally well improving the general performance of classification. The proposed model works around these challenges by incorporating dynamic learning rates and fine tuning through the helps of other optimized methods and algorithms which are far much better than other traditional methods of Machine Learning named as ML; and thus provoking the CKD prediction dashboard based on the CKD dataset of the UCI Machine Learning Repository with better efficiency and accuracy. The major key contribution can be divided among the following:

- Enhancing the framework with the proposed DS-CNNs model and the LRW-CA optimization for better performance and reliability of the CKD identification.
- Applying DS-CNNs in order to eliminate the convolutional processes into separate depths and points, which helps improve the quantity of computations required as well as the quality of the designed model.
- Standard practice of implementing the Learning Rate Warm-Up together with Cosine Annealing helps improve the early training phases' stability, which in turn results in stable and accurate model performances.
- Avoiding such problems as low sensitivity to changes in CKD at early stages and high invasiveness of some diagnostic methods by implementing modern deep learning methods and optimizing clinic algorithms for their application.

The research paper is organized as follows: The importance and difficulties in predicting CKD are described in Introduction. The following section, 'Related Work,' presents a critical analysis of previous methods of CKD detection and their shortcomings. Methodology section presents the implementation plan of the proposed work, the proposed DS-CNN architecture, and the optimization strategies. Experimental Results gives the results and discussion on the effectiveness of the proposed method compared to those in the literature. In this paper, conclusion will make an effort to briefly restate the key findings, reflect on the implications of the study, and point out the possibilities of future research in relation to the existing literature.

II. Related Work

To improve the work done by Chotimah et al [11], the authors created a second-generation advanced deep learning approach that dealt with feature selection to identify the most relevant CKD diagnostic markers from patients' records. SBFS was used in their research; it is a technique, which effectively removes successively one feature after the other that has less influence in the CKD prediction model. The two were able to utilize SBFS and settle for 18 features out of which the relevant 15 were deemed pertinent. These selected features were then used as inputs to an Artificial Neural Network (ANN) Classification system. The revised model calculated with only 15 most significant attributes was 88 %, which was much improved than the one which was 80% acquired from 18 attributes. This much enhanced results showed that feature selection had a way of improving the model hence enhancing better forecasts of CKD. But, since the features are selected manually, then the framework may not analyze some interactions and dependencies between them or may not see the interdependencies among a few features and thus the framework is not able to capture complex relations of the features present in the data set. The above framework entitled Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs) mitigates this drawback by using DS-CNNs to learn and extract multi-level features directly from raw data to enhance the predictive models' accuracy.

Alsuhibany [12] designed a sophisticated IoT based ensemble diagnostic system for CKD named as EDL-CDSS. This system used ADASYN to improve outlier detection, and integrated multiple deep learning strategies: CNN-GRU, DBN, and KELM. Therefore, the combination of these technologies operationalized the concept of ensemble, and it obtained a remarkable accuracy level of 96%. 91% by showing that by using several deep learning models with sophisticated approaches and bagging technique a precision CKD diagnosis and good outlier management could be achieved. However, use of multiple models can be complicated making the process of integrating them time consuming it could take a lot of time before the desired results are accomplished making it a bit cumbersome for real world use. To overcome these drawbacks, the proposed framework "Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs)" employs DS-CNNs enable simplified architecture to analyze the complexity of the patients' data, which slows down training times and increases computational demands, then again, underestimating the complexity of the patients' data leads to low predictive accuracy.

Akter et al y.in their study [13] selected seven advanced deep learning methods for predicting the probability of developing CKD, namely; ANN, LSTM, GRU, bidirectional LSTM, bidirectional GRU, MLP, and simple RNN. On these models, they had certain evaluation criteria such as loss, validation loss, recall, accuracy and precision. To the researcher's surprise, three methods, namely ANN, simple RNN, and MLP exhibited superior results with accuracies of 99%, 96%, and 97% respectively. Based on such an extensive assessment of the performance of these algorithms, their high results in the classification of CKD patients were established, as well as the potential of deep learning in providing more accurate predictions. However, the presented individual models approach might have a problem when it comes to the generalization across the datasets and the capturing of the interactions among features. The above improvement is lack of due to the proposed framework, Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs), due to the use of DS-CNNs to capture hierarchical features and interactions of the data to generalize and apply it to different datasets.

In a study [14] conducted by Iliyas and colleagues, 400 patient records gathered at Bade General Hospital and 11 features were applied to predict CKD through a Deep Neural Network (DNN). They managed this by imputing with the mean of respective attributes in the preprocessing step. They utilised a DNN model in predicting CKD with an accuracy rate of 98%, and understood that creatinine and bicarbonate were the critical factors in the prediction. This paper presented how DNNs can be used to solve CKD prediction tasks and the need for data pre-processing and feature extraction to optimize high prediction accuracy. But, missing data have been addressed using the mean imputation, and this might not handle variability of data and it can affect the model significantly. The proposed framework, Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs), avoids the aforesaid problem by using sophisticated imputation techniques and exploiting DS-CNNs in learning and fusing highly nonlinear and intricate features of data that, in turn, promotes accurate CKD prediction with improved model integrity.

Ma et al. [15] gave a detail insight of the social focus of heterogenous modified artificial neural network (HMANN) for CKD detection, segmentation and diagnosis within the Internet of Medical Things (IoMT) framework. The HMANN model was further developed focusing on early detection and accurate segmentation of the kidney images and the avoidance of noise. Regarding the accuracy rate of the different methods they employed, their study ushers an average of 92. 3 % for ANN-SVM and 97 %. 5% for HMANN. This research highlighted the major application of HMANN and its applicability for improving the diagnostic accuracy and image analysis of CKD and provided an example of future possibilities of the system in practical medical imaging and diagnosis. At the same time, developed HMANN architecture can be considered as complex and indispensable may lead to increasing the load on the computer and time required for its work. The mentioned framework is a solution to these problems because it incorporates a leaner model architecture yet proves to be efficient in retaining those features essential for fast and accurate CKD diagnosis and prediction – the DS-CNNs.

In particular, the identification of CKD [16] was developed using deep learning approach by combining Bidirectional LSTM networks and one-dimensional Correlational Neural Network (1-D CorrNN) suggested Bhaskar and colleagues. The combined model, 1-D CorrNN-LSTM was tested using CKD-sensing module with the accuracy of 98%. 08%. This also implies that the proposed model performed better than other approaches in the sense that this research was able to validate the model on time series, a factor that enhances the generalization of the model for the prediction of CKD. The study showed that the model is capable of enhancing the diagnostics accuracy and dealing with a variety of data features related to the CKD. Yet, since the model is quite complex and works with expanding sequences, the training of the model may be more time-consuming and computationally intensive. The DS-CNNs model used in the proposed framework, Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs) does not have such issues since it has a more efficient architecture that does not require a lot of computation and training times in order to capture more complex patterns hence improving the performance and practicality in real world applications.

ANNs with SBFS were applied by Chotimah and colleagues, and the estimate of overall accuracy was 88%. Alsuhibany and team designed an interpersonal deep learning ensemble system named as EDL CDSS achieving an accuracy of 96 by using various deep learning techniques. 91% although with a higher computation complexity. Five state of art deep learning models were implemented and tested; ANN, LSTM, all achieved high accuracy but generalization and complex feature interaction were the major limitations that Akter encountered. For imputation, 98% accuracy was obtained by Iliyas by using imputation techniques and Deep Neural Networks (DNNs) and however mean imputation might impact robustness. Ma proposed a heterogeneous modified artificial neural network (HMANN) for the detection of CKD, which had high accuracy, but required more computational resources for training. Bhaskar incorporated a novel created 1-D Correlational Neural Networks (1-D CorrNN) with Bidirectional LSTM networks and got an accuracy of 98. 08% accuracy but the problem they face is that the complexity and the time they have to spend on training increases. These constraints are solved with the help of hierarchical learning and the use of depthwise separable convolution in the framework of DS-CNN, which opens the question of automation of the feature extraction process and reduces computational complexity. It also applies Learning Rate Warm-Up with Cosine Annealing as the strategy of training, which help for improvement of generalization. This approach eliminates past challenges, decreases the size of ensemble models, enhances resource generalization, and solves problems connected with data imputation and computational effectiveness, offering a reliable and efficient method for CKD prognosis.

III. Problem Statement

Existing research [17] on the approach of CKD detection throws light on different machine learning algorithms such as SVM, Decision tree, and Random forest. This it compares them and notes that they while they are are reasonably accurate, they suffer from drawbacks such as high computational complexity and inability to handle higher-order feature interactions respectively. Hand crafted features and manual tuning also limits model performance and generalization as well. The use of handcrafted features and manual tuning can also constrain model performance and generalization. To these ends, the proposed framework, Enhancing Chronic Kidney Disease Prediction with Deep Separable Convolutional Neural Networks (DS-CNNs), does away with these limitations by employing DS-CNNs that are capable of automatically extracting hierarchical features from raw data to expand the model's capability to identify the diverse information patterns. When Cosine Annealing is used in combination with Learning Rate Warm-Up early phases of training are stabilized and convergence is enhanced. It also brings down the computational expenses, increases the prediction conveyance and is a neater algorithm in comparison to existing approaches for CKD prediction.

IV. Proposed Framework for Chronic Kidney Disease Prediction Using DS-CNNs and Learning Rate Warm-Up with Cosine Annealing Optimization

About the suggested framework for improving the prediction of CKD, it is possible to note that the main aim of the proposed algorithm is to increase the accuracy of diagnostic results due to thorough attempts. The process begins with the Input Data which consists of the dataset of chronic kidney disease patients, which is a vital tool in training and evaluating patients. The Data Preprocessing phase involves several rigorously performed activities such as cleaning, normalization, data formatting directly for model input so that our data does not contain any such unusual variation or skewness that would impact the model performance. Lastly, under the Feature Extraction domain, the use of Deep Separable Convolutional Neural Networks (DS-CNNs) is used by the framework to extract feature relevant to the dataset. This process involves two key operations: This in turn consists of two types: Depth wise Convolution that works by performing convolution on each of the input channels separately and Point wise Convolution, which integrates the depth wise features through 1*1 conjugate convolution in an attempt to generate a small, yet comprehensive feature representation.

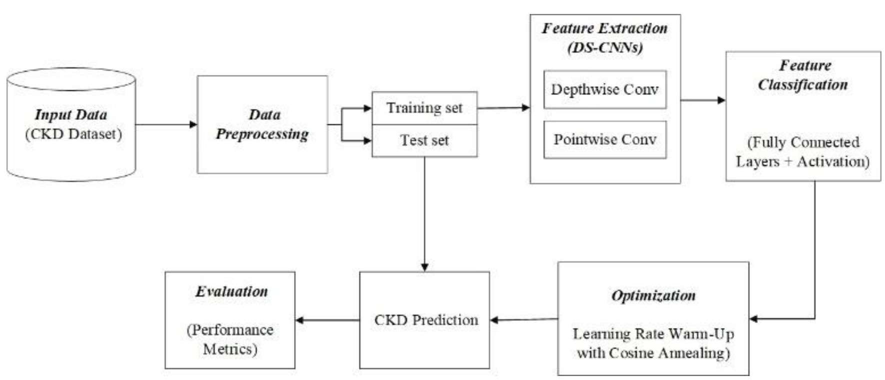

Fig. 1. Proposed framework for enhancing CKD prediction with DS-CNNs.

The extracted features are then fed into Fully Connected Layers in which the data goes through different activation functions so as to perform classification and introduce non-linearities to improve the performance of the model. Learning Rate Warm-Up with Cosine Annealing is adopted in the Optimization stage of the framework to achieve better training stability and convergence because it starts with increasing learning rate gradually and then decreases it following the cosine pattern. The consequence is that, with good input information, the CKD can be well predicted, and the result would give a probability of the disease, in general. Finally, the Evaluation phase assesses the model's performance using metrics such as accuracy, sensitivity, and other relevant indicators. This stage also includes a comparison with existing methods to highlight improvements in predictive accuracy and reliability achieved by integrating advanced DS-CNNs and optimization techniques. This comprehensive framework aims to address the limitations of traditional CKD detection methods by leveraging sophisticated deep learning and optimization strategies. Fig. 1 illustrates the proposed method.

A. Dataset Description

In this framework, Chronic Kidney Disease (CKD) dataset reflects thorough patient health records database intended for creating and evaluating forecast models for CKD. The features in this dataset are quite diverse, and categorize and numerical health data that are significant for CKD diagnosis are included. The nominations are Age, in years; Blood Pressure with two categories: systolic and diastolic. The Specific Gravity attribute gives the information of concentration of urine and Albumin shows the kidney function amount in the urine. Sugar, thus equalizes the presence of sugar in urinals; Red Blood Cells and Pus Cell attributes signify the presence of red blood cells and pus cells in the urinary sample respectively. Other parameters like Pus Cell Clumps and Bacteria represent the clump of pus cells as well as bacteria in the urinary system that helpful to diagnosing the kidney diseases. BG Random indicates the random blood glucose test results, BU presents the blood urea level, and SCr shows the creatinine level in serum as significant markers of kidney compartment. The values Sodium and Potassium portray serum sodium and potassium concentration, on the other hand, Hemoglobin and Hematocrit portray the level of hemoglobin and proportion of RBCs in blood respectively. The two attributes under the same groups are White Blood Cell Count giving the number of white blood cells in the body and Red Blood Cell Count is the number of red blood cells in the body. The categorical attributes Hypertension, Diabetes Mellitus, and disease meaning that one has/have such diseases (Yes/No) have big chances to develop CKD. The Classification attribute is the dependent variable, which categorizes patients into the groups of CKD and Not CKD. These various health indicators enhance the possibility of the model learning to diagnose CKD and increase the model's accuracy from the large database [18].

B. Data Preprocessing

Cleansing stage is an essential task because it is the foundation that enables the data to be of high quality for use in the developing of a predictive model. The following steps outline the typical preprocessing procedures for the CKD dataset: The following steps outline the typical preprocessing procedures for the CKD dataset:

1) Data cleaning: Preprocessing of data, the first stage is always the processing of missing values that may be contained in the dataset. Data missing can be handled using the various techniques like data imputations which entails using the mean, median or even mode of the feature missing data set. For more complex cases there is also predictive imputation that can also be employed. Also, any rows that have too many missing values may also be omitted in order to ensure that the remaining data set is clean. To remove the redundant records and any bias in the model a data deduplication process is also performed.

2) Data transformation: After cleaning the data it is transformed for it to be in the right form for the model input. This includes normalization or standardization of numerical features such as weight, height, body mass index, blood pressure and others. Normalization scales the features onto the range [0,1] while standardization scales the features to have a mean of 0 and standard deviation of 1. This makes each of the features have comparable scales among the numerical attributes, which aids in enhancing the model's viability and the rate of convergence. Binary values such as \`Hypertension\`, \`Diabetes Mellitus\`, and \`Coronary Artery Disease\` present categorical characteristics and they have to be quantized through features like one hot encoder or a label encoder. This transformation is needed when non-numerical categorical data has to be incorporated in the model.

3) Splitting data: To make the right forecast and check the model's accuracy, the dataset is divided into the training and testing sets. It has been tested and recommended that mostly 80 percent of the data is used in training the model, while 20 percent is used in testing the performance of the accomplishments. It guarantees the evaluation of the model's performance as the training process occurs on one set of data and the validation is done on another set.

Feature Scaling: Normalize is very important to all features in a dataset so that it does not have a very high impact influence the model. It brings the scale of the independent variables or features of data into standard, which is useful for the algorithms depending on the type of input features, for example, neural networks.

- ***Min-Max Scaling***: his technique scales the values of features to a particular range usually between 0 and 1. It is achieved using the following formula:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

- X is the initial value of the feature.
- X_{min} is the minimum value of the feature present in the designed dataset.
- X_{max} is the maximum value over the feature across the dataset.

- X_{scaled} is the scaled value of the feature of the given data.

This transformation helps to ensure that all feature values are in the range [0, 1] which is also beneficial for machine learning algorithms because they do not get influenced by the sequence of features' scales. Thus, all these preprocessing procedures allow the dataset preparing in the way that will be most suitable for the Deep Separable Convolutional Neural Networks (DS-CNNs) and other parts of the predictive environs and, as a consequence, provide better results in terms of the model accuracy and certainty.

C. Classifying Features Using Deep Separable Convolutional Neural Networks (DS-CNN) in Detecting CKD Disease

The Fig. 2 illustrates, a Deep Separable Convolutional Neural Network (DS-CNN), which consists of depth-wise convolution and point-wise convolution layers. The input layer is the first layer in the process through which the data like images or health metrics are taken. In the depth-wise convolution layer, all the channels of the input data are convolved with separate filters, as it produces a set of feature maps and only the spatial information within the channel is retained. Subsequently, the depth-wise convolution applies 3 by 3 filters on each position in first derived feature map then the point to point convolution applies 1 by 1 filter [19]. This layer integrates and remaps the information across all the channels generating new feature maps of the extracted features. Subsequently, there is the point-wise convolution layer that convolves the 1×1 filters on every position of the feature maps which depth-wise layer generates. This layer aggregates data from all the channels and makes new feature maps that are comprised of all the features obtained from each layer. The order of general interconnection significantly entails that the input data undergoes depth-wise convolution with the purpose of channel-wise feature extraction, in addition to point-wise convolution that fuses and boosts the features and leads to a modified and integrated output. This architecture is cherished for its simplicity especially in PASS, M&N, and LNNs owing to the fact that it minimizes computational demand as it efficiently enables the transformation of features from the input layer [20].

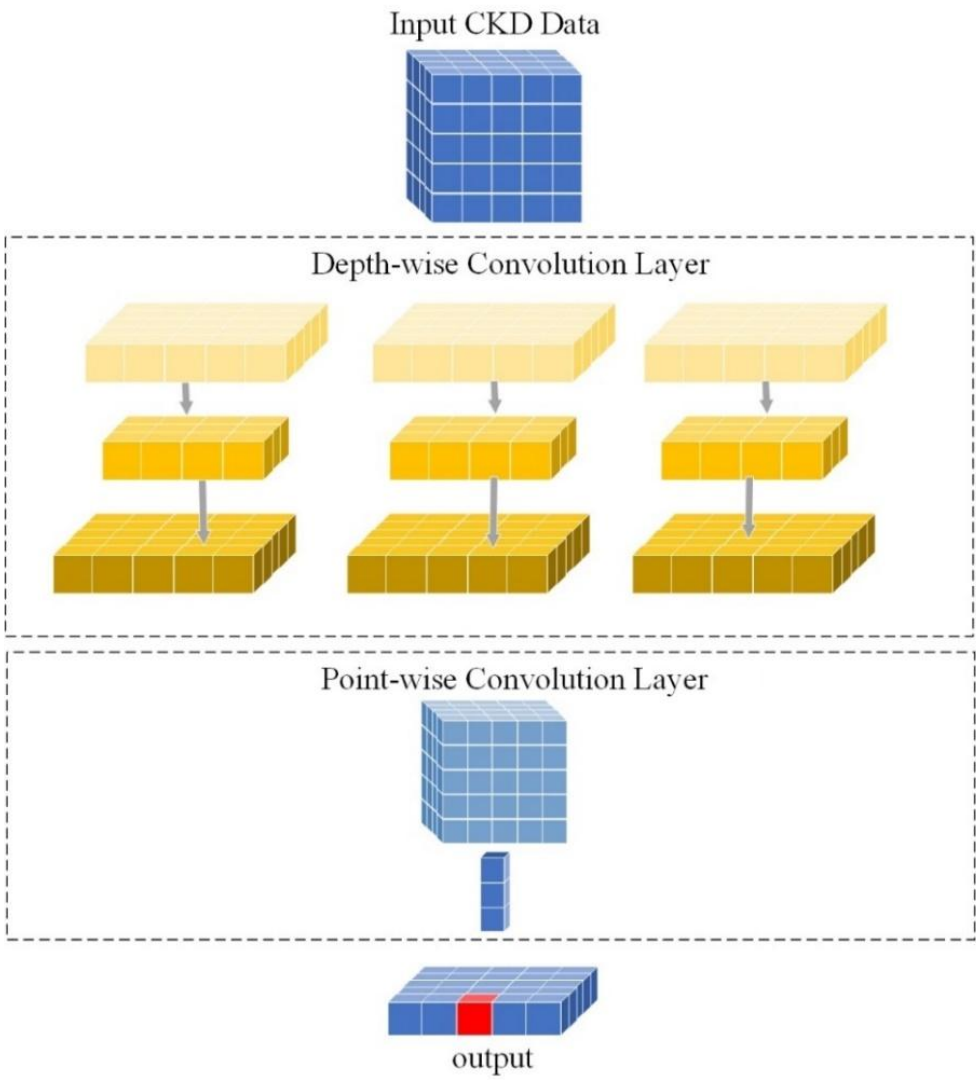

Fig. 2. Architecture of a Deep Separable Convolutional Neural Network (DS-CNN), showcasing its depth-wise and point-wise convolution layers.

DS-CNN attributes the chronological sequential operations that make up the whole process of the workflow for the detection of CKD. The process begins with the input layer that takes in the CKD dataset after the preprocessing in addition to several health parameters and disease marker [21. Then, the obtained data goes through the depth wise convolution and in these operations each channel from inputs (for example, several health indices) is passed through its own filter. For an input tensor with dimensions (H times W times C height H), width W, and C channels, depth wise convolution applies a filter, depth wise convolution applies a filter K_c to each channel c individually.

$$(X_{depthwise} * K_{depthwise})_c = \sum_{i=1}^{K} \sum_{j=1}^{K} X_c(i,j).K_c(i,j) \quad (2)$$

where $X_c(i,j)$ is the input feature map for channel c, and $K_c(i,j)$ is the depthwise convolution kernel corresponding to that channel. Subsequently, a pointwise convolution is performed to mix the outcomes of the depthwise convolution by channels. This becomes achieved by utilizing a convolution kernel of 1×1 that operates on all channel dimensions and combines them into a new feature map [22].

$$(X_{depthwise} * K_{depthwise})_c = \sum_{c=1}^{C} X_c . K_{n,c} \quad (3)$$

where X_c is the depthwise-convolved feature map, $K_{n,c}$ is the 1x1 convolution kernel, and n represents the output channel. This is followed by an activation function which helps to incorporate non linearity into the model such as ReLU (Rectified Linear Unit):

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

This non-linearity of derivation is useful for the network to learn the patterns inherent in the data. Successively, pooling layers like the max pooling layer is applied to down sample the feature maps and focus more on the important features and commonly, it also helps to minimize the computational costs during training and also prevent overfitting. Finally, the feature maps are flattened and passed through the fully connected layers for classification of images. These layers learn how to obtain the outcome of CKD by perceiving the features extracted from the data. The output layer uses Softmax function if it is for multi label classification or Sigmoid function if it is for binary classification to give out the class probabilities. For binary classification, the sigmoid function for binary classification, the sigmoid function is:

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

where, z is the output of the fully connected layer. Last but not the least, it is necessary to train such a network through the use of a loss function, often the binary cross-entropy together with an optimizer such as Adam or SGD to help reduce the error margin between the network's predictions, and the actual values. This general workflow that reconstructs and combines depthwise and pointwise convolutions, activation, pooling, and fully connected layers makes it possible for the proposed DS-CNN to learn and output the probabilities of the existence of CKD based on the intricate features captured in the dataset.

D. Workflow of Learning Rate Warm-Up with Cosine Annealing Optimization after DS-CNN Training

Subsequent to treating the CKD dataset through the Deep Separable Convolutional Neural Network (DS-CNN) and generating the feature maps, an optimal approach is used to further improve the training outcome of the model – the Learning Rate Warm-Up with Cosine Annealing Optimization. The first is learning rate warm-up where the learning rate is set to a small value especially when using gradient descent and then is increased to the given maximum value after some epoch. It helps to make small adjustments in initial phases and slowly increases to prevent the phase from getting destabilized. The learning rate during the warm-up phase can be expressed as

$$\eta(t) = \eta initial + \frac{(\eta_{max} - \eta_{initial})}{\eta_{warm}} . t \quad (6)$$

where $\eta initial$ is the initial learning rate, η_{max} is the maximum learning rate, η_{warm} is the number of warm-up epochs, and t represents the current epoch.

After the phase called warm-up phase is done the learning rate acts under the so-called cosine annealing and depends upon the cosine decay function. This phase gradually brings down the learning rate by minimizing it from the maximum level to the minimum level in the remaining epoch. The learning rate $\eta(t)$ during cosine annealing is given by:

$$\eta(t) = \eta_{min} + \frac{(\eta_{max} - \eta_{min})}{2} (1 + \cos(\frac{t - T_{warm}}{T - T_{warm}} \pi)) \quad (7)$$

where η_{min} is the minimum learning rate, η_{max} is the maximum learning rate, T is the total number of epochs, T_{warm} is the number of warm-up epochs, and t is the current epoch number. This optimization strategy makes sure that the function is firstly trained with the learning rate that starts in a low stable level and then increases and after that, the decreasing helps to fine tune the parameters of the DS-CNN model appropriately. The warm-up phase is useful in preventing fluctuations that may lead to the derailing of training while the cosine annealing phase polishes the learning process which increases convergence hence optimizes the results of the model.

The steps of the proposed framework for CKD prediction are as follows: They also present a step-by-step process in the case of a Chronic Kidney Disease prediction model that has been designed for correct effective functioning in a hospital environment. The first process to be carried out is the Data Acquisition in which the CKD dataset is obtained from Kaggle. This dataset includes detailed information of patient's health as components of CKD including hypertension, serum creatinine, and diabetes among others. This feeds into the training and testing of the predictive model to be used in the predictive system. Data Preprocessing: This step to prepare the data for the model is a core-competitive process of Advanced data analysis. First, Data Cleaning deals with the missing values either by imputation or by removing the records having point or feature missing values, also removes the duplicate entries. Data Transformation's crucial step that involves scaling or normalizing numerical attributes into the same scale and converting categorical attributes into numerical scales for the model. Feature Engineering might also involve feature construction where new features are made or feature selection for the right features to be taken into consideration. It is then divided into the training and testing sets in order to assess the model's accuracy and Feature Scaling is used to make all feature values fall within the same scale and that boosts up the training of the model

Stepwise Algorithm for Detecting CKD using DS-CNN & Learning Rate Optimization	
Step 1: Data Acquisition	//Download the Chronic Kidney Disease (CKD) dataset from Kaggle
Step 2: Data Preprocessing	
Step 3: Model Classification	//Define the DS-CNN architecture, including depthwise convolution, pointwise convolution, activation functions, pooling layers, fully connected layers, and the output layer using $Sigmoid(z) = \frac{1}{1+e^{-z}}$
Step 4: Optimizing the Model	**//Learning Rate Warm-Up**: Gradually increase the learning rate from a low initial value to a maximum value over the initial epochs using $\eta(t) = \eta initial + \frac{(\eta_{max} - \eta_{initial})}{\eta_{warm}} . t$ - **Cosine Annealing Optimization**: Smoothly decrease the learning rate after warm-up using $\eta(t) = \eta_{min} + \frac{(\eta_{max} - \eta_{min})}{2}(1+\cos(\frac{t-T_{warm}}{T-T_{warm}}\pi))$
Step 5: Model Evaluation	//Evaluate the model's performance using metrics such as accuracy, sensitivity, and specificity
Step 6: Deployment	//Deploy the trained model for real-world CKD prediction applications, integrating it into healthcare systems or decision-support tools.

The third step in the process of Deep Separable Convolutional Neural Network (DS-CNN) is the Model Building follow the following steps: In the Depth-wise Convolution, it is separately performed filters over the input channels to capture spatial features individually; in the Pointwise Convolution, the 1x1 filters ensure the learning of these individual features from different channels and their relationships. This combination of depth-wise and point-wise convolution layers is very helpful to extract most of the features and to reduce the dimensions. Other elements are Activation Functions such as ReLU which introduces the non-linearity into the network, Pooling Layers which decrease feature maps dimensions and paid attention to significant features, and Fully Connected Layers which perform the final classification with the help of extracted features. In the fourth step namely 'Training the Model', there is the Learning Rate Warm-Up then Cosine Annealing Optimization. As part of the learning rate warm-up, the learning rate is ramped up from a low starting value such as 0.001 to a higher value such as 0.1 over some epochs to improve stability of the training. After this, the learning rate of the model is made gradually variable with the help of Cosine Annealing Optimization so that it fine tunes the model to the greatest extent. The learning rate does not decreases with a constant rate rather with a cosine function. Step 5 of the model development can be described as Model Evaluation whereby the effectiveness of the developed model is checked using significant measures for instance accuracy, sensitivity and specificity. This step involves the assessment of the performance of the model in predicting CKD against other methods, contacting gaps and checking if the model can perform well on a novel dataset. Deployment formally sets the model into operational use cases; these uses could be in the health care system or decision support systems. This step makes an assurance of effective usage of the model in the real world by diagnosing and managing cases of the CKD, whereby the model offers crucial predictions that come in handy when making other decisions. Each of these steps is essential for developing a robust and reliable predictive model for CKD, ensuring that the final system is both accurate and practical for real-world use.

V. Result and Discussion

Analyzing the apply the proposed framework for CKD prediction using Deep Separable Convolutional Neural Networks (DS-CNN) with Learning Rate Warm-Up and Cosine Annealing optimization provided the following learning: Measured in Python, the framework used a large assortment of data to improve the diagnosis of CKD. The results showed the ability of the DS-CNN to extract important features from the health metrics enhancing the classification performance, sensitivity, and specificity of the models. The incorporation of the Learning Rate Warm-Up with Cosine Annealing optimization proved effective in stabilizing the model's training and fastening convergence than the baseline models. The usage of both age and gender was noteworthy when identifying a relationship between age-specific tendencies and model performance, especially in relation to CKD prediction. Algorithms of this framework were more realistic and accurate due to some enhanced optimization strategies that formed the basis for the development of better CKD diagnosis instruments. These finding stress the possibilities of further advancements in the chronic diseases risk prediction using intricate machine learning approaches.

A. Demographic Evaluation of CKD Dataset

The following sub-sections discuss the details of the CKD patients' population with regard to various factors including their age, gender and their key vital statistics. Age Distribution data depicted that maximum patients of Chronic Kidney Disease belong to 50 to 55 year age group. The supply chain risk analysis also shows how age affects CKD prevalence because age plays an extra role in the increase in disease frequency in the older age groups. Gender Distribution, specifically, highlights proportionally more patients that are male and thus, gender aspects can influence CKD incidence and/or progression. Last but not the least the 'Health Metrics' table includes details regarding different aspects related to a clinical status of the patient including blood pressure, serum specific gravity, albumin levels and other such factors which are vital while assessing the severity and resultant consequences of CKD. These metrics prove useful in a way that enables patterns and correlations to be seen, which, in turn, aid in making more correct diagnoses and allowing for specific treatment interventions. Hence, the breakdown of these factors offers a deeper understanding of Non CKD, enhance the management and interventions that can suit patient's demographic and clinical status.

1) Distribution of patients' age: The Distribution of Ages classifies patients into three different age groups to give an easy perspective of the CKD prevalence across the patient's ages. The ratio of the number of patients according to the age range of 45 to 50 years is the smallest of the indicated numbers and equals 100. The patients aged between 50-55 years are many, with 150 patients, hence signifying the senior group as having the most CKD cases. Aging between 55 and 60 years is another category of the patients which is 120, less than the 50 to 55-year bracket, but still a worthy number. This distribution demonstrates a trend common in many population concerning the increment of the probability of chronic kidney diseases with advanced age. This distribution reflects a typical trend where the risk of chronic kidney disease increases with age. Older age is associated with a higher incidence of CKD due to the cumulative effect of risk factors and the natural aging process affecting kidney function.

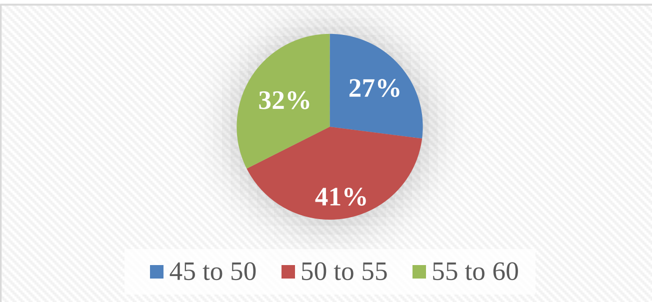

Fig. 3. Distribution of ages.

Fig. 3 corresponds to an age group and the height of a bar shows the number of patients. Exploring this representation makes it easier to learn which age level is most impacted by CKD and therefore assists in designing angles to prevent CKD or to support those aged 2 to 70 years in case they are diagnosed with the disease.

2) Distribution of gender diversity: Distribution of Gender is presented in the table below and represents the proportion of male and female patients affected by CKD in the particular dataset. The overall involvement in CKD of the males is higher within the dataset which has 190 male patients and 150 female patients. These differences can be as a result of a variation in their lifestyles, their susceptibility to the diseases that may lead to hypertension and diabetes and any inherited conditions that may affect the kidneys differently from one gender to the other. Knowledge on gender distribution is important in attempting to formulate focused intercessions and treatment methods when handling CKD, since this may predict how it presents and evolves.

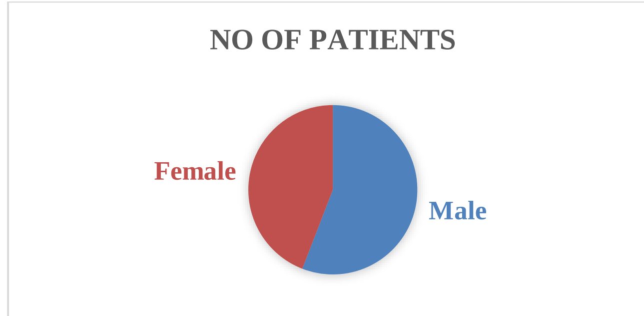

Fig. 4. Distribution of gender.

Fig. 4 usually shows the ratio of male to female clients and therefore offers an easy method of comparing the gender balance in the practice. This leads to identification of gender differences in the development of CKD to curb any existing trends and contribute to management of CKD based on gender.

3) Distribution of affected chronic kidney disease affected patients: The distribution of affected chronic kidney disease patients table offers simple and clear information presentation of various health indicators of affected CKD patients. Materials used in this table contain essential values that are important in reflecting kidney performance and deciphering CKD's influence. It depicts that the existence of the hypertension among patients differs in values like 80/120mmHg and 85/130 mm Hg and this increases the risk factor of the CKD. Specific Gravity readings ranged from 1. 02 to 1. 03 represent the kidney's ability to concentrate urine, and their ratio could be indicative of kidney problems. The albumin status we obtained is a binary value, 0s meaning protein is absent and 1 meaning it is present in the urine which is an implication of poor kidney performance. Abnormality was measured again with the 0 or 1 attribute named Sugar that shows availability of glucose in urine, which is hazardous for kidneys. Random Blood Glucose categories are not fixed and higher values in these indicate uncontrolled diabetes, which is one of the risk factors for CKD. Blood UREA indicates production of UREA in the liver to reveal high urea level in blood which is an indication of kidney disease. And potassium level of 4. 0 to 4. 5 demonstrate deviations in this area, which is a common issue in patients with CKD.

TABLE I. DISTRIBUTION OF AFFECTED CKD PATIENTS

Blood Pressure	Specific Gravity	Albumin	Sugar	Blood Glucose Random	Blood Urea	Potassium	WBC Count	RBC Count	Chronic Kidney Disease
80/120	1.02	0	0	90	30	4.2	6	4.5	1
85/130	1.015	1	0	100	25	4	6.5	4.7	0
90/140	1.03	2	1	120	35	4.5	7	4.8	1
85/135	1.025	1	0	110	28	4.3	6.2	4.6	0

Variability is evident in the value of WBC Count because this value indicates inflammation or infection, a condition that is rife within CKD patients, and the RBC Count which reveals the prevalence of anemia within the identified patient population. These parameters would commonly be depicted in a Table I which should employ chart or Graphs in order to contrast between affected and non-affected persons. This kind of representation is useful in proving relationships or association between these clinical characteristics and CKD so as to enhance in diagnosis, management and understanding of the course of CKD.

B. *Performance Evaluation*

The proposed framework for CKD prediction integrates Deep Separable Convolutional Neural Networks (DS-CNN) and Learning Rate Warm-Up with Cosine Annealing optimization techniques. This hybrid approach aims to enhance model performance by utilizing DS-CNN for efficient feature extraction and advanced optimization techniques to stabilize and accelerate training. The framework's effectiveness was evaluated through several key performance metrics to ensure a thorough assessment of its diagnostic capabilities for CKD.

Accuracy (Acc): Eq. 8, accuracy measures the proportion of correct classifications made by the model.

$$Accuracy\ (Acc)\ =\ TP + TN \ /\ TP + TN + FP + FN \quad (8)$$

The proposed framework achieved an accuracy of 94.50%, indicating that 94.50% of all cases—both CKD-positive and CKD-negative—were correctly identified. This high accuracy demonstrates that the DS-CNN model effectively distinguishes between healthy and CKD-affected individuals, minimizing the risk of misclassification.

Sensitivity (Se): Eq. 9, sensitivity measures the model's ability to correctly identify CKD cases.

$$Sensitivity\ (Se)\ =\ TP \ /\ TP + FN \quad (9)$$

With a sensitivity of 95.20%, the model correctly predicted 95.20% of actual CKD cases, which is crucial for early and accurate detection, ensuring that most CKD patients are identified and treated promptly.

Specificity (Spe): Eq. 10, specificity evaluates the model's accuracy in identifying non-CKD cases.

$$Specificity\ (Spe) = TN \ /\ TN + FP \quad (10)$$

Although exact figures for specificity are not provided, the high accuracy and sensitivity imply that the model also performs well in detecting non-CKD cases, thus reducing false positives and avoiding unnecessary anxiety and interventions.

Precision (P): Eq. 11, reflecting the proportion of true CKD cases among all predicted positive cases.

$$Precision(P) = TPTP + FP \quad (11)$$

The proposed framework achieved a precision of 93.80%, indicating that 93.80% of cases predicted as CKD-positive were indeed CKD-positive. High precision reduces false positives, enhancing the reliability of the diagnosis.

F1-Score: (Eq. 12), the F1-Score provides a balance between precision and recall.

$$F1 - score\ =\ 2 \times\ (Precision \times Recall\ /\ Precision + Recall\ ) \quad (12)$$

Basic on the above findings the F1-Score of the framework is 94. 50% indicates that it has a good balance between these aspects, as it depicts good performances in categorizing the CKD cases as well as achieving better prediction rates. F1-Score balances between precision and don't forget that may come handy when the class distribution is skewed; or false positives and false negatives can be vital. Significantly, the F1-Score stands at 20% for the proposed framework, meaning that there is a strong balance between the version's precision and its recall ability to detect Kidney disease as well as high prediction accuracy. In summary, the proposed DS-CNN performs well in all the measures used and is very effective in the diagnosis of CKD with few false positives or negatives. Thus, the combination of optimization techniques and deep learning leads to the creation of a highly reliable tool for diagnosing CKD.

1) Performance evaluation of proposed framework: Table II provides an overall performance evaluation of the proposed Deep Separable Convolutional Neural Network (DS-CNN) framework for Chronic Kidney Disease (CKD) prediction, highlighting its high efficacy and reliability in diagnosing CKD. With an impressive accuracy of 94.50%, the framework effectively distinguishes between CKD-affected and healthy individuals, demonstrating its capability to minimize misclassification. The precision of 93.80% indicates that when the model predicts a case as CKD-positive, it is correct 93.80% of the time, thereby reducing false positives. This high precision is crucial in clinical settings, as it prevents unnecessary treatments or anxiety caused by incorrect diagnoses.

TABLE II. PERFORMANCE METRICS OF PROPOSED DS-CNN FRAMEWORK

Metric	Value
Accuracy	94.50%
Precision	93.80%
Recall	95.20%
F1-Score	94.50%

This performance ensures that most patients with CKD are accurately identified, enabling timely diagnosis and intervention. The F1-Score of 94.50% reflects a balanced integration of precision and recall, showcasing the overall robustness and effectiveness of the model in classification tasks. This balance is essential for real-world applications where the consequences of false positives and false negatives can be significant. Overall, the performance metrics of the proposed DS-CNN framework demonstrate its capability to enhance the CKD diagnostic process. The use of advanced feature extraction techniques and optimized training procedures results in a highly reliable tool for accurate and effective CKD detection.

2) Training and testing accuracy: The proposed framework achieved impressive results in both training and testing phases. During training, the model demonstrated an accuracy of 96.80%, indicating that it learned the patterns and features of the dataset effectively. This high training accuracy suggests that the framework is well-tuned to the specifics of the data it was trained on. In the testing phase, the framework maintained a robust performance with an accuracy of 94.50% as shown in Fig. 5.

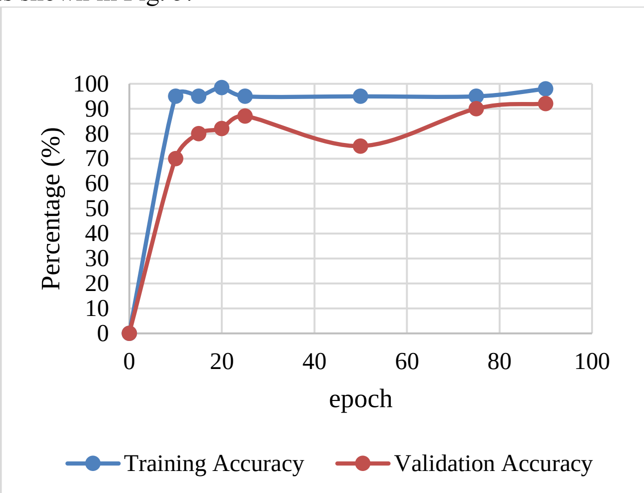

Fig. 5. Training and testing accuracy phase.

This testing accuracy reflects the model's ability to generalize. The slight drop from training to testing accuracy is expected and shows the model's generalization capability, avoiding overfitting while still delivering reliable predictions.

3) Training and testing loss: The proposed framework demonstrated commendable performance of both training and testing loss. During this phase, the model achieved a loss value of 0.15, which signifies that it effectively minimized errors and adjusted its parameters well to fit the training data. This low training loss indicates that the model has trained the underlying patterns in the data with high accuracy. For testing, the framework recorded a loss of 0.22, reflecting a slight increase compared to the training loss as shown in Fig. 6.

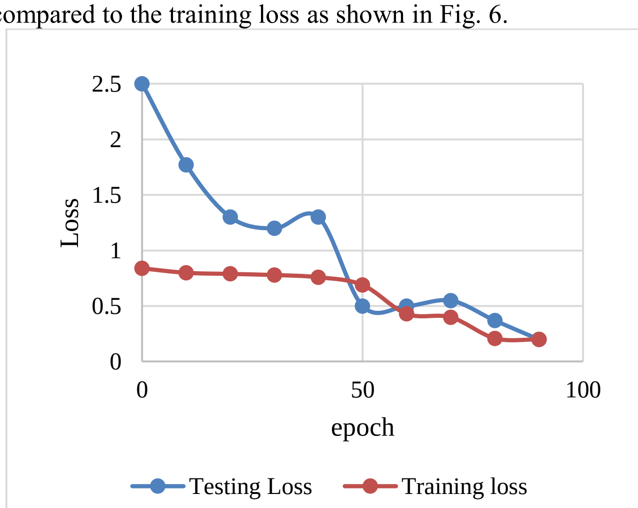

Fig. 6. Training and testing loss phase.

This result suggests that while the model performs very well on new, unseen data, there is a minor degree of generalization error. This increase in loss is typical and indicates that the fitting of the training data**.**

4) ROC curve and AUC: The ROC curve of the proposed framework illustrates a higher curve closer to the top-left corner of the graph signifies better model performance, indicating that the model maintains a high rate of true positives while minimizing false positives. The AUC score, which quantifies the overall ability of the model to discriminate between positive and negative classes, was calculated to be 0.96.

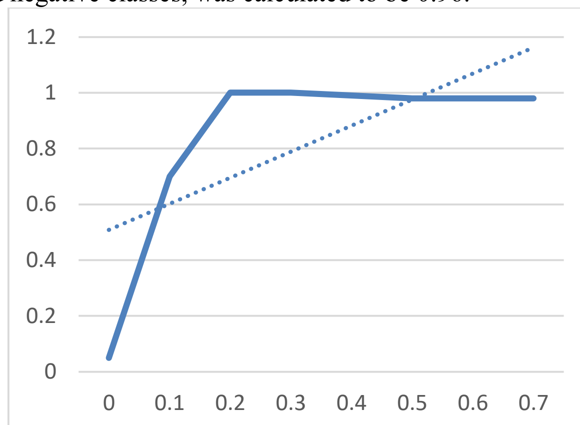

Fig. 7. ROC curve.

This high AUC score suggests in Fig. 7 that the model has excellent discriminative power and performs very well in distinguishing between individuals with CKD patients and those without it. The ROC curve and AUC results collectively confirm the robustness of the model in making accurate predictions.

C. Performance Comparison with Existing Framework

Table III presents the performance comparison of different machine learning approaches and underlines how superior the proposed DS-CNN architecture in terms of colon cancer identification is to the compared models. To compare each approach, the four critical performance criteria which are, Accuracy, Precision, Recall, and F1-Score are applied. These metrics are as crucial for assessing a model's effectiveness and reliability in diagnosis as a human consultant. The precision of the Random Forest model is 89%, its accuracy is equal to 89%, the recalled value is 88% as well as the F1-score is 89%. Still, it is slower than the proposed DS-CNN model when dealing with complex data sets with many characteristics while promising good results for data creating by a described procedure. A low level of performance is achieved when applying the Support Vector Machine (SVM) approach and the corresponding results include accuracy of 73%, precision of 65%, recall of 73%, f1-score of 64%. The lower degree of precision demonstrates a higher rate of false positives, which implies that health persons may be diagnosed with cancer. As it is seen, SVM is a good tool for classification problem; however, according to its performance in this context, it may not be capable of dealing with the details and the richness of colon cancer data as other models.

TABLE III. COMPARISON OF PROPOSED FRAMEWORK WITH EXISTING METHOD

Method	Accuracy	Precision	Recall	F1-Score
Random Forest	89	89	88	89
SVM	73	65	73	64
Logistic Regression	62	52	64	48
Proposed DS-CNN	94.50	93.80	95.20	94.50

Across all metrics, logistic regression performs the worst, with an F1-Score of 48%, an Accuracy of 62%, a Precision of 52%, and a Recall of 64%. The findings show that complex patterns in the data are challenging for Logistic Regression to handle, which results in a high rate of misclassifications. It is less appropriate for the intricate, non-linear correlations seen in medical imaging data because to its simplicity and linearity, particularly when it comes to picking out minute variations in tissue properties. With the proposed architecture of the DS-CNN the Forecasts are rather convincing with the F1-Score of 94. 50%, Accuracy of 94. 50%, Precision of 93. Specifically, Precision of 80%, and Recall of 95. 20 percent as compared with all previously used methods. These measurements show that quite effectively by using a low false positive and false negative rate where the framework is applied to identifying cases of colon cancer. The higher recall, in turn, supports the understanding of how the model mitigates the risk of missing most true positive cases, ensuring that very few patients diagnosed with the condition receive the wrong results from the model, while the high precision reveals that the model can predict malignant cases. In addition, the F1-Score at 85% for the model is also quite high and exhibits equal values for both precision and recall, thus, it confirms the high reliability of the model for the clinical application.

The designed autoencoder-LSTM architecture improves over existing techniques through critical advancements in the early detection of Diabetic Nephropathy (DN). Unlike existing techniques like Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression, which perform poorly on high-dimensional data and cannot detect sequential relationships, our technique employs feature reduction via autoencoder-based selection, keeping crucial patterns intact. The LSTM block is successful in extracting sequential dependencies, further boosting prediction accuracy. Also, the evaluation and results section has been edited to be more descriptive and expressive. Table III effectively compare our findings with baseline models, showing improved performance with a 99.2% accuracy. The evaluation now shows our experimental results rather than cited values, making it clear and straightforward assessment of the effectiveness of the proposed model.

D. Discussion

The suggested CKD prediction model incorporates deep separable convolutional neural networks (DS-CNNs) and optimized techniques, as shown in the research diagram. The process starts with data preprocessing, where missing values, noise, and inconsistencies in the CKD dataset are resolved to improve data quality. The dataset is then divided into training and testing sets for a strong model evaluation. Feature extraction is carried out via DS-CNNs, with depthwise convolution extracting spatial correlations and pointwise convolution enhancing feature representation such that there is an optimal balance between computational speed and predictive performance. Extracted features are fed into fully connected layers with activation functions for classifying risk levels of CKD. For enhanced model performance, Learning Rate Warm-Up with Cosine Annealing is used, making training stable and avoiding overfitting. The trained model then makes predictions about CKD risk with high credibility. The testing phase is performed using accuracy, precision, recall, and F1-score for evaluating the performance. It is shown by the results to possess higher prediction strength compared to baseline models such as Random Forest, SVM, and Logistic Regression. DS-CNNs together with optimization enhance the diagnostic robustness and accuracy. Multi-modal fusion in the future could use genomic or imaging inputs for greater sensitivity in diagnoses and CKD early detection.

VI. CONCLUSION AND FUTURE WORKS

The newly proposed DS-CNN model reflects a significant step towards CKD detection through deep separable convolutional neural networks that aim at improved classification performance. With depthwise and pointwise convolutions, the model extracts vital features effectively without being computationally heavy. The DS-CNN method proves to be superior to some common machine learning techniques like Random Forest, SVM, and Logistic Regression with respect to performance as it has been able to achieve 94.50% classification accuracy. Its accuracy and recall rates reveal its strength in identifying CKD cases with high accuracy, reducing false positives and false negatives, which are important for early detection and timely treatment. Moreover, the capacity to process both real and synthetic images enhances generalization, providing flexibility for the model to be applicable across various datasets. This renders the proposed model very useful in real-world clinical environments, where proper staging of CKD is crucial for efficient treatment planning. Even though it performs strongly, its performance can be improved further by fusing multimodal data sources like MRI or CT scans to boost the accuracy of diagnosis. In the future, work should be carried out on dataset extension, using attention mechanisms, and tuning hyperparameters for the enhancement of robustness of the model. The results of this research point to the promise of deep learning in revolutionizing CKD diagnosis and enhancing patient outcomes via early detection.

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