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Ensemble & Hybrid Model for Chronic KidneyDisease Classification with Machine and Deep Learning Approaches

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Abstract
chronic kidney disease is most serious worldwide health concern with a high fatality rate, Early detection of chronic kidney disease enables patients to get medication while the condition is still mild, and disease progression can be halted. Due to its quick recognition execution, machine learning and deep learning may be used to successfully achieve this goal. The present approach predicts chronic diseases for a particular area and community. This recommended methodology uses machine learning techniques including ANN, Naive Bayes, Decision Tree, Naive bayes, KNN, and Support Vector Machine and Hybrid models to dissect the errors caused by the setup models. There will be grading for accuracy, recall, f-measure, and precision. This technology will thus be used to detect illnesses using a variety of complex medical data.

Keywords — Chronic Kidney disease, Deep learning. CNN, SVM, ANN

Introduction

The kidneys that are impacted by CKD gradually degrade until they are unable to efficiently filter blood any more. The body started storing more dangerous and waste materials as a result, which raised the risk of high blood pressure, heart attacks, and stroke. The exact findings inside the CKD prediction reflect the usage of imputation to fill in the missing data given that it is based on diagnostic classifications of the samples.

Kidney Disease is the result of recurrent acute kidney injury (AKI) events, which causes permanent renal tissue damage. It should be noted that although when it comes to AKI is a kind of self-defense, it also has an impact on the renal cell by increasing the likelihood of fibrosis. By assessing imaging characteristics, ultrasound (US) can predict early renal function in various kidney or ureter structural diseases and is a non-invasive, practical diagnostic tool. For instance, clinical investigations have attempted to quantify changes in estimated glomerular filtration rate using kidney size, cortical thickness, and cortical echogenicity (eGFR). For instance, the finding in shows a statistically significant positive correlation between eGFR and mean renal length ($r = 0.66$) and between eGFR and mean cortical thickness ($r = 0.85$). Along with the changes in renal form and geometry already mentioned, the texture of renal tissue in the US has also altered.

The picture also suggests that renal function has changed. However, in order for doctors to gain expertise in the in-depth interpretation of renal US images, they often need to undergo extensive training. As a result, the findings of interpretation may not be objective since they heavily depend on the physicians' own subjective cognition.

Convolutional neural networks have been using deep learning techniques for computer vision problems in recent years (CNN). In contrast to conventional techniques, CNN models automatically extract features, and often extract much more characteristics than conventional techniques. Due to its strong feature learning capabilities, CNN is increasingly being used to tackle more intricate issues. It also performs well when analysing medical pictures. Lin et al. employ CNN to assess the level of inflammation in the long head of the biceps tendon using a US picture as an example. However, In this study we have used Convolutional neural networks(CNN) and hybrid models for better prediction of chronic kidney disease.To achive this we have used the opensource MRI set datascan images which is from an open source and provides better results.

Literature Survey

A poroelastic deformation model was used to estimate kidney malformation fields from derived and original dynamic time series. Numerous quantitative measures reflecting pressure gradients, volumetric deformation, and shear were built using the fields of deformation. Biopsies were used as the gold standard on eight individuals. Based on the results of the biopsy, it is concluded that arteriosclerosis significantly links absolute malformation, gradient of pressure and normalised changes in volume.

According to the National kidney Foundation, 10% of the world's population has Chronic Kidney Disease (CKD) and many people die due to insufficient treatment.

Zhen-Yi Tang [1] implemented the techniques VGG16, InceptionV3, MobileNetV2, DenseNet121, and DPCNN in the earlier studies, with accuracy ratings of 79.2%, 78%, 75.4%, 78.4%, and 85.6%, respectively. Previously they have used IFTA prediction dataset, we used MRI set datascan images which is from an open source and provides better results.

We employed ResNet and ensemble model - CNN+SqueezeNet and ANN, as well as a hybrid model that combined CNN-SVM , CNN-DT, CNN-KNN, CNN-NB. The ANN Algorithm provides the best results with 85% accuracy. We obtained accuracy values of 85% for ANN, 55% for ResNet, 45% for CNN+SqueezeNet, and 76.67% for the hybrid model (CNN, SVM), 73.33% for the hybrid model (CNN,DT), 66.67% for hybrid model (CNN,KNN), 76.67% for hybrid model (CNN-NB).

Since we have got less accuracies for the ensemble models we've developed a hybrid model which provides better results than above.We have implemented the hybrid model and ensemble models to predict the chronic kidney disease more accurately.

Proposed Work

A. Dataset Gathering
B. Data Pre-processing
C. Build Model
D. Evaluation

Dataset Gathering

The proposed method is described below for collecting data, screening experts, and augmenting the data. Additionally, we show how we develop our databases. This step includes the collection of data from the recent records and analysing the data for the prediction of results. Dataset consists of images.

Data collection:

200 photos were obtained from the kaggle database, which is the world's largest community offering a data platform for machine learners to exploit. And there are 3 folds of Chronic Kidney disease.

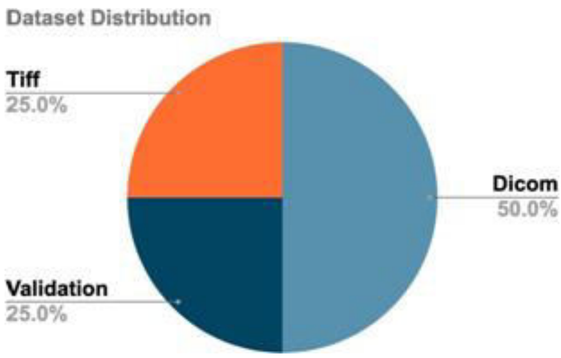

Fig 1 : Original dataset distribution

In our data set we had 100 image records of Dicom , 50 image records of Tiff and 50 image records for validation. By this using this dataset we first implemented SqueezeNet model , Ensemble model of CNN and Resnet, ANN,VGG and Hybrid Model.

Data Pre-Processing

In this step of the implementation. The dataset is being checked for corrupted data and the missing values and for the null values. With the incorrect data the results cannot be accurate. And the find out missing values can be filled with the pre-processing techniques and make the dataset with the unique values. The missing values in the attributes like BMI, Insulin, Blood pressure etc are filled with the normalised values.

Model Building

This is the crucial step in the complete implementation of the model. In this step the Deep learning techniques are used to predict the Chronic Kidney Disease. These Deep learning techniques include ANN, VGG, SqueezNet, CNN, Ensemble model(Resnet & CNN), Hybrid model(CNN-SVM-DT-KNN- NB).

Chronic Kidney Disease Prediction using machine and Deeplearning algorithms
Step1: Import the required libraries of all the functions.
Step2: Link the Google Colab file to the drive.
Step3: Now import the kidney disease dataset.
Step4: Pre-processing the dataset and make the dataset unique and with no null values.

Step5: Testing and the Training the model.
Step6: Implementing the machine and Deep learning algorithms.
Step7: Prediction of results and the accuracy, confusion matrix.

Evaluation

Evaluation is the last stage of prediction of results in the working model. In this we can predict the results of the Kidney Disease using the accuracy of Machine and Deep Learning algorithms.

Model Building

CNN with SVM

A hybrid of CNN and SVM is a combination of two different machine learning models that are used together to improve the performance of image classification tasks.

The SVM is then trained on the feature maps extracted by the CNN. The SVM uses these feature maps as input, and it tries to find the best hyperplane that separates the different classes of images. The SVM uses the feature maps to learn a decision boundary that separates the different classes of images.

During the testing phase, new images are passed through the CNN to extract their feature maps, and then these feature maps are passed to the SVM to make the final classification decision. The hybrid model uses the extraction of feature capabilities of the CNN and the classification capabilities of the SVM to increase the performance of image classification tasks.

The main advantage of using a hybrid of CNN and SVM is that it combines the strengths of both models. The CNN is efficient in the extraction of complex features from the input images, while the SVM is able to make accurate classification decisions based on these features. Additionally, the CNN can be pre- trained on a large dataset, which can be used to improve the generalization of the SVM.

CNN with Decision Tree

A working model of a hybrid CNN and decision tree would involve several steps: Pre-processing: Prepare the image dataset by resizing, normalizing, and splitting it into training and test sets. Feature extraction: Use a pre-trained CNN, such as VGG16 or Model evaluation: Use the test dataset to asses the performance of the hybrid model. Metrics such as accuracy, precision, recall, and F1-score can be used to evaluate the performance of the model.
Fine-tuning: If the performance of the model is not satisfactory, we can fine-tune the decision tree by adjusting the parameters or by using a different decision tree algorithm. Deployment: Once the model is trained and fine-tuned, it can be deployed in a production environment to classify new images.
It is worth noting that the specific implementation and the architecture of the CNN and decision tree may vary depending on the dataset and the problem at hand. Additionally, it is also important to consider the interpretability of the model in the final step of the model building.

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CNN with KNN
A hybrid of CNN and KNN (K-Nearest Neighbors) is a combination of two different machine learning models that can be used together to improve the performance of image classification tasks.
The working principle of the hybrid model is to first use the feature extraction from input images using CNN, and then use the KNN algorithm to classify the image based on these features.

The CNN is trained on images contained in the large dataset, and its main purpose is feature extraction from the input image. The output of the last convolutional layer of CNN is called feature map, and it represents a compact representation of the image that captures the most important features.

The main advantage of using a hybrid of CNN and KNN is that it combines the strengths of both models. The CNN is able to extract complex features from the input image, while the KNN algorithm is able to make accurate classification decisions based on these features by taking into account the context of the neighboring examples. Additionally, the KNN algorithm is simple and computationally efficient.

CNN with Naïve Bayes
The working process of CNNs is on the convolution operation, which involves applying a set of filters to an image. These applied filters are designed to identify patterns or features in the image, such as edges, shapes, or textures. By applying these filters to the image, the CNN is able to extract features from the image at different scales.

Naive Bayes, on the other hand, is a probabilistic algorithm that is commonly used for classification. The algorithm is based on Bayes' theorem, It implies that the likelihood of an event is multiplied by the previous probability of the event to get the likelihood of the event occurring.

In summary, CNNs working principle is based on convolutional and pooling layers that extract features from images at different scales, while Naive Bayes is a probabilistic algorithm based on Bayes' theorem that uses the probability distributions of the features to estimate the probability that a given input belongs to each class, assuming that features are independent of each other.

ANN
An Artificial Neural Network (ANN) is a computational model inspired by the structure and function of biological neurons. It consists of layers of interconnected artificial neurons, also called artificial "nodes" or "units", which are organized in a structure called the network architecture.

The basic building block of an ANN is the artificial neuron, which takes input from other neurons and produces an output. The input to a neuron is a weighted sum of the outputs from the neurons in the previous layer, which is then passed through an activation function to produce the output.

The working model of a feedforward ANN can be described asfollows:
1. The input is fed into the input layer, which consists of neurons that represent the input features.
2. The input is then passed through one or more hidden layers, which consist of neurons that learn to extract useful features from the input.
3. The outcome of the last hidden layer is connected to output layer, which consists of neurons that produce the final prediction.
4. The output of the network is compared to the desired output and the error is calculated.
5. The error is then propagated backwards through the network to update the weights of the neurons and improve the network's performance.
6. The process is repeated multiple times, with different sets of input data, until the network's performance is satisfactory.

It's worth noting that ANNs can be trained by different techniques such as

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backpropagation, and the architecture of the model can be adjusted to solve the problem at ease.

VGG

The VGG (Visual Geometry Group) architecture is a convolutional neural network (CNN) that is commonly used for image classification tasks. The model is known for its use of small convolutional filters (typically 3x3) and stacking multiple convolutional layers, which enables the network to learn more detailed and complex features from the image input.

The process is repeated multiple times, with different sets of input data, until the network's performance is satisfactory.

It's worth noting that VGG networks typically use a very deep architecture with multiple convolutional layers, and this can make them computationally expensive to train. However, the use of small convolutional filters and max-pooling layers allows the network to learn detailed and robust features from the input image.

SqueezNet

SqueezeNet is a convolutional neural network (CNN) architecture that is designed to be lightweight and efficient while still achieving competitive performance on image classification tasks.

The working process of SqueezeNet is on the idea of reducing the number of parameters in the network while still achieving competitive performance SqueezeNet's fundamental building piece, fire modules, is made up of two sub-modules: a squeeze layer and an expansion layer. In order to limit the amount of feature maps, the squeeze layer is a 1x1 convolutional layer, while the expand layer is a combination of 3x3 and 1x1 convolutional layers that increases the number of feature maps. This architecture allows the network to learn both detailed and abstract features from the input image, while keeping the number of parameters low.

By using a combination of 1x1 convolutional filters and fire modules, SqueezeNet is able to significantly fewer parameters are used in the network while still achieving competitive performance on image classification tasks. This makes SqueezeNet a lightweight and efficient alternative to other CNN architectures such as ResNet and VGG.

CNN

The working principle of a convolutional neural network (CNN) is based on the concept of learning a hierarchy of more complicated characteristics by employing convolutional layers to extract information from the input picture.

A CNN typically consists of multiple layers, including fully connected layers, convolutional layers, and pooling layers. Features from the input picture are extracted by the convolutional layers. Each convolutional layer consists of multiple filters, also known as kernels or weights, that are used on the source picture. In order to execute a dot product between the filter weights and the picture, the filters move across it. The image pixels in that region they are currently covering. This results in a feature map that encodes the presence of certain features in the image. The filters are learned during the training process, and they are typically small (e.g. 3x3 or 5x5) in order to learn fine-grained features.

RESNET and CNN Ensemble Model

The working principle of a ResNet (Residual Network) is based on the idea of using residual connections to allow very deep neural networks to be trained effectively. Convolutional neural networks (CNNs) that employ residual connections are known as ResNet , also known as shortcut connections, to allow very deep networks to be trained effectively. A residual connection is a connection that bypasses one or more layers and directly adds the input to the output of a layer.

The ensemble model can be created by training multiple CNNs independently making a final forecast by adding their guesses together. This can be accomplished by employing strategies like majority voting, in which the resultant forecast is based on the majority of the

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individual models' projections or weighting, where the predictions of the individual models are weighted based on their performance.

The working principle of a ResNet and CNN Ensemble model is to leverage the strengths of each model help enhance the ensemble model's overall performance. The ResNet is used to train deep neural networks effectively and the CNN ensemble model is used to combine multiple models.

Results and Discussion

TABLE 1 Accuracy comparisons

Methods	Accuracy
ANN	85
VGG	80
SqueezNet	45
CNN	80
RESNET & CNN Ensemble model	55
er	76.67%
CNN-DT	73.33%
CNN-KNN	66.67%
CNN-NB	76.67%

ANN

Fig. 2: validation accuracy followed by confusion matrixfor ANN

VGG

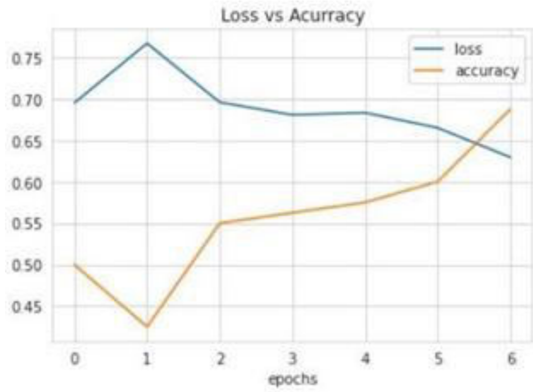

Fig. 3: validation accuracy followed by confusion matrix forVGG

SqueezNet

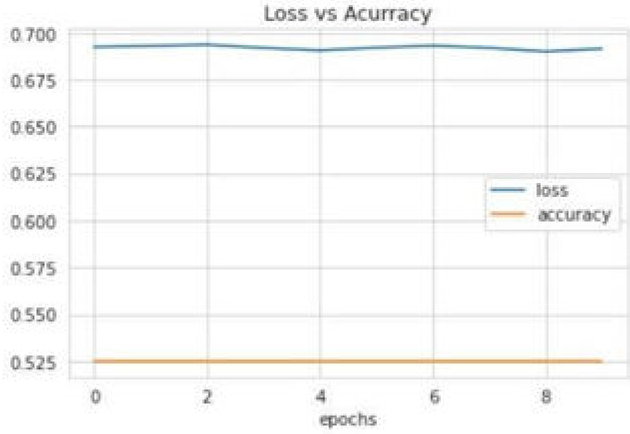

Fig. 4: validation accuracy followed by confusion matrix for SqueezNet

CNN

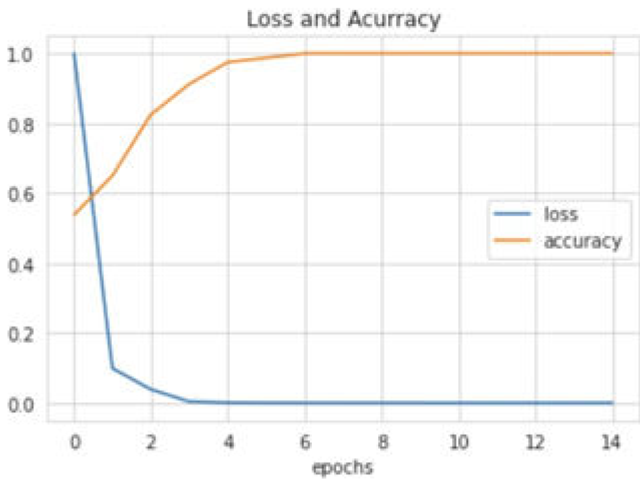

Fig. 5: validation accuracy and confusion matrix for CNN

RESNET & CNN ensemble model

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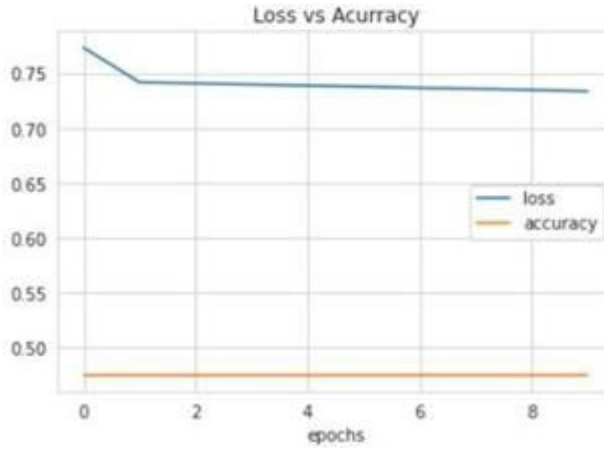

Fig. 6: Train vs validation accuracy and loss graph followed byconfusion matrix for resent 101

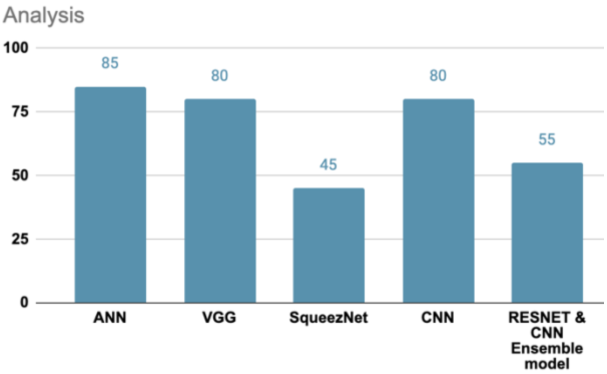

Fig. 7: Comparative analysis of accuracies

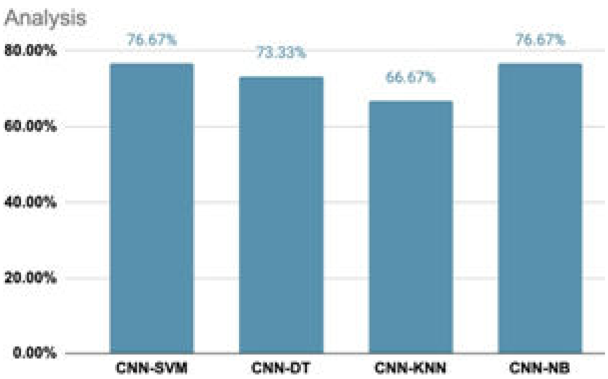

Fig 8: Comparative analysis for Hybrid Models

Conclusion

Earlier so many models have been developed by many great people in the field chronic kidney detection. The first main concern of the researchers is the point of accuracy. In order to increase the accuracy in the detection of chronic kidney disease, new methods should be implemented over the old ones. This research proposes a machine learning based Ensemble model by using Machine learning algorithms.

With this study and analysis, we have used many ML and DL algorithms on the considered dataset and the implementation had been performed using many algorithms of which ANN produces the maximum accuracy of 85.00%, and also the Ensemble and Hybrid models which is higher accuracy than the existing accuracies in the field of detection of kidney disease. Mostly the ratio of deaths can be minimized if disease is found in the starting stages and accordingly preventive measures can be taken to rid of the chronic kidney disease. In future it has the high scope, and this work can be forwarded to some extent that how the non-chronic kidney people can be affected by chronic kidney disease and what are the risk factors in the coming few years.

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