Predicting Chronic disease using Kernel Based Xception Deep Learning Perfect

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Abstract

In this investigation, we fill in missing values with the use of a unique sequential approach to data scaling that combines resilient scaling, z-standardization, and min-max scaling. Next, m-Xception does the classification by employing a different architecture than the initial convolutions. Furthermore, the convolution layer is broken down into depth-based sub-layers that are linked together by linear residuals. This productive model was trained using a two-stage transfer learning strategy. The kernel values of the proposed model are optimally selected for large-scale cases with the use of a Squeaky Wheel Optimisation (SWO) metaheuristic. The projected model was tested by simulation on the canonical CKD dataset and assessed statistically. The findings suggest that a fully automated method of assessing CKD severity is feasible. These results give support for the hypothesis that a unique approach to problem resolution may be achieved by combining predictive modelling with the most recent deep learning developments. This may be tested in the context of renal illness and beyond..

Keywords: Squeaky Wheel Optimization; Chronic Kidney Disease; Cloud Computing; Min-Max Scaling. Modified-Xception;

DOI Number: 10.48047/nq.2017.15.2.1075 **NeuroQuantology 2017; 15(2): 292-297**

Introduction

When combining software and hardware, IoT is frequently used. Low-power applications, such as refrigerators, smart watches, wrist bands, and the like, have seen broad adoption of the Internet of Things, as opposed to high-power devices like monitors, tablets, tools, mobile phones, etc. [1]. Only a few of today's air purifiers and air conditioners utilise a microprocessor and sensor devices. The Internet of Things (IoT) is making considerable strides towards full integration with the Cloud Computing (CC) paradigm, which has several advantages over traditional approaches [2]. Advanced clinical and sensing equipment is desperately needed in the medical profession, which is one of the most promising fields [3]. It's getting harder to catch dangerous diseases early on as the cost of necessary equipment climbs. These measures are crucial for preventing death. In order to verify the presence of life-threatening diseases in people, the proposed study heavily emphasises an online Clinical Decision Support System (CDSS) that employs IoT devices [4]. The Internet of Things generates a plethora of data for clinical applications, and data science is an essential tool for making use of this data.

Electronic health systems (e-Health) employ WSNs to monitor patients remotely [5]. A large number of the currently available smart watches make exaggerated claims about their capacity to track your health in great detail. However, a medical professional couldn't use one of these smartwatches to establish a diagnosis. If a vital sign is off, only then will it provide a warning [6]. We need to

use a dependable medical monitor to track the patient's vitals at this time. Some common examples of medical devices are pulse oximeters, blood pressure monitors, thermometers, electrocardiogram (ECG) machines, and heart rate monitors (HRM). Vital sign monitoring is a cornerstone of healthcare monitoring systems [7, 8]. Vital signs are monitored in the intensive care unit using healthcare monitoring systems [9]. That's why it's so important to have healthcare monitoring systems in place for early disease detection [10]. One of the biggest drawbacks of a healthcare monitoring system is the high upfront cost. The high expense of treating and monitoring chronic diseases creates an urgent need for cost-effective healthcare solutions [11]. This is true in both low- and high-income nations.

Here are the remaining parts of the paper: Here is how the paper is structured: In Section 2, we provide our literature study; in Section 3, we describe our proposed model in depth; in Section 4, we discuss our evaluations of the results; and in Section 5, we offer a conclusion and summary.

2. Related works

Swain et al. [18] developed a machine learning algorithm to foresee the beginning of chronic renal illness using publicly available data. A generic model was constructed from this dataset after it through a number of data preparation steps. Before imputed values are generated, the attributes are scaled and normalised using the SMOTE method. Using the fewest available observations, the chi-squared test establishes which features are essential and highly related to the output. Multiple supervised learning approaches are often integrated to construct a robust machine learning model. In comparison to other used learning strategies, support vector machine (SVM) and random forest (RF) achieved the highest levels of test accuracy (99.33%) and false-negative rate (98.67%). However, when both methods were put through 10 rounds of cross-validation, SVM came out on top.

As part of their novel ensemble DL approach to CKD detection, Alsekait et al. [19] employ a number of feature selection methods to zero down on the most informative characteristics. Our optimal feature selection for CKD is also explored in terms of its clinical relevance. Pretrained deep learning (DL) models are combined with the metalearner model, the support vector machine (SVM), to form the proposed ensemble model. Patients from the UCI machine learning repository, numbering 400 in all, were employed in the research. The results demonstrate that the proposed model is more effective than alternatives in predicting CKD. The recommended model, by using the mutual_info_classi method to choose features, produced the best results.

Venkatesan et al. [20] used ML techniques on a publicly available dataset to classify and predict CKD. The CKD dataset, including 400 samples, was downloaded from the freely available Irvine ML Repository. When deemed superior. Measures of effectiveness for ML algorithms include accuracy, recall, precision, and the F1-measure. The results shown that XGBoost achieved the highest accuracy (98.00%) when compared to the other ML algorithms. This study puts forth a methodology that might help policymakers estimate the global burden of CKD. The idea has the potential to facilitate better resource allocation, patient-centered care, and heightened surveillance of those at risk.

For the purpose of early diagnosis and prediction of CKD, Venkatrao and Kareemulla [21] presented a novel hybrid deep learning network model (HDLNet). The Deep Separable Convolution Neural Network (DSCNN) was proposed in this research as a deep learning-based strategy for the detection of CKD in its earliest stages. Capsule Network (CapsNet) can extrapolate more processing attributes from features known to indicate renal disease. The Aquila Optimisation Algorithm (AO) is used to pinpoint important traits in order to expedite the classification process. Classification efficiency is improved by the necessary qualities with just a little increase in processing effort. The DSCNN approach of classifying kidney illness into CKD and non-CKD is fine-tuned with the use of the Sooty Tern Optimisation Algorithm (STOA).

Validation is performed using the CKD dataset from the UCI machine learning library. Precision, recall, positive predictive value, negative predictive value, and specificity are all measures of the efficacy of the suggested CKD classification approach. Additional experiments support the claim that the suggested method outperforms the existing standard for CKD classification.

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2.1. Problem Statement

Early detection of this kind of CKD is vital, and may even save the patient's life. Experts in the medical field used numerous core methods, including physical examinations and laboratory testing (including blood and urine tests), to obtain exact insights into renal disease diagnosis. The glomerular filtration rate (GFR) is calculated from the blood sample, and it may be an indicator of kidney health. The albumin level in the urine is a good indicator of the health of the kidneys. Developing robust and generalizable diagnostic models that can support medical specialists and deliver correct and quick recommendations is essential in a time when promising data sources might aid in medical diagnosis. The field of medical diagnostics has recently benefited from the use of machine learning (ML) to the development of effective models capable of making correct and fast conclusions. The goal of deep learning (DL), a subfield of machine learning, is to discover hidden relationships within a dataset by performing a series of operations during training. DL is a multilayer DL model with the potential to process nonlinear data, which has far-reaching consequences for medical applications..

3.2.1. Data Scaling

To begin, we use resilient scaling, which reduces the impact of extreme values and improves the system's robustness. To achieve this, we took the difference between the third and second quartiles and divided it by the difference between the first and third quartiles (Q3 Q1). Here is the equation that describes the relationship::

$$Robust\ Scaling(x) = \frac{x-Q_2}{Q_3-Q_1}$$ (1)

After that, we employed z-score standardisation to get a standardised distribution by subtracting the mean (m) and dividing by the standard deviation (). Here is the equation that describes the relationship::

$$Z-score\ Standardization(x) = \frac{x-\mu}{\sigma}$$ (2)

Lastly, min-max range (usually 0 to 1). ($x_{\min}$) and dividing by the range($x_{\max} - x_{\min}$). This can be proprietary by the following equation:

$$Min-Max\ Scaling(x) = \frac{x-x_{min}}{x_{max}-x_{min}}$$ (3)

3.2.2. Data Splitting

Partitioning data is essential for effective model testing and generalizability, two factors crucial to machine learning [28]. The first step is to divide the data into test and training sets.:

$$Dataset = training\ data + testing\ data$$ (4)

In this study, we used 80% of the data for training purposes and 20% for evaluating our model. The model is then evaluated on fresh data to determine how well it generalises to the new data set used in training...

3.3. Proposed Model for Classification

Both CKD and normal classifications can benefit from this method since it boosts model performance without adding complexity to the underlying network. The model's convolution layer makes use of linear residuals to connect convolution layers that are spatially isolated in depth. The first flow is built atop the Xception network, which acts as a feature extraction network. Second, it uses two independent convolution layers to create an intermediate flow. There have been eight iterations on the base layer. At last, we reach the exit flow stage. In this final layer, the thick layer really forms...

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$$Log\ S\ of\ tmax = \frac{\log(\exp(x))}{\sum \exp(x)} = x - \log((\exp(x) log(\sum \exp(x))))$$ (5)

Logarithmic The loss function of the proposed model is optimised using softmax of variable x. Over-fitting may be avoided during training thanks to a Regularise feature that regulates the layers.

$$Loss = \frac{1}{n}\sum_1^n L_i + \lambda R w_i^2$$ (6)

where L = L × log(avg(R)).

3.3.1. SWO-Based Heuristic Framework

One point in the solution space represents one possible solution to the problem at hand, and another point in the priority space represents the relative importance of those solutions. After the point in the priority space has been updated by reassigning the order of vessels depending on their expenses, the construction step comprises discovering a collection of feasible solutions under the stated processing order for vessels. Prioritising costly vessels is important to this strategy. To find the best answers, SWO iteratively adjusts the problem's priority and solution spaces.

4. Results and Discussion

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (7)$$

$$Recall = Sentivity = \frac{TP}{TP+FN} \quad (8)$$

$$Specificity = \frac{TN}{FP+TN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$F1\ score = 2\frac{precision \times recall}{precision+recall} \quad (11)$$

4.2. Performance Analysis of Projected model

Techniques	Precision	Recall	F1-Score	Accuracy
Proposed model	98.33	97.34	98.16	97.56
ResNet	89.33	94.64	94.38	94.82
AlexNet	96.67	90.23	95.80	96.22
VGGNet	95.33	96.33	97.33	94.13

The Validation Analysis for the 80:20 model proposal is summarised in Table 2. The proposed model achieved an F1-score of 98.16 and an accuracy of of 98.33 and a recall range of 97.34. After those adjustments, the ResNet model achieved an F1-score of 94.38, precision of 89.33, recall of 94.64, and accuracy of 94.82. After those adjustments, the AlexNet model's accuracy was 96.22 percent, its precision rate was 96.67 percent, its recall range was 90.23 percent, and its F1-score was 95.80 percent. The F1-score for the VGGNet model ended up being 97.33, the precision rate was 95.33, the recall range was 96.33, and the accuracy was 94.13.

The Dell laptop utilised for the experiments, analyses, and evaluations included 16 GB of RAM, a 1.50 GHz CPU, and Windows 10 on the x64 architecture. The SWO optimizer was used to train all networks for 10-30 iterations with a batch size of 64 and a focal loss function = 2. An initial 10-epoch learning rate of 1 x 106 was followed by a 30-epoch learning rate of 1 x 107.

4.1. Performance metrics

In this analysis, participants with CKD were given a positive value, whereas those without CKD were given a negative one. The results of the machine learning models were evaluated and illustrated using the confusion matrix. The construction of a confusion matrix is depicted in Figure 9 [30

Table 4: Investigation of numerous classifiers on diverse epochs

Methods	10 Epochs			
	Training Acc. %	Validation Acc. %	Training Losses	Validation Losses
DBN	75.6	75.4	88.14	88.41
RNN	82	82	76.44	73
CNN	83.24	84	73.1	71

ResNet	87.1	87	74	77
AlexNet	88.54	88	89	82
VGGNet	94.11	95.32	71	73
m-Xception	96.78	95	62.1	55

Table 4 above depicts the examination of numerous classifiers throughout multiple time periods. Training accuracy for the DBN model was 75.6%, validation accuracy was 75.4%, and loss for training was 88.14% and loss for validation was 88.51% during the course of the 10-epoch analysis. After that, the RNN model hit an accuracy of 82 during training, 82 during validation, 76.44 during loss during training, and 73 during loss during validation. The final results for the CNN model were an accuracy of 83.24 in training, 84 in validation, a loss of 73.1 in training, and 71 in validation. After that, the ResNet model hit an accuracy of 87.1 in training, 87.5 in validation, and a loss of 77 in validation. Training accuracy for the AlexNet model was 88.54 percent, validation accuracy was 88 percent, training loss was 89 percent, and validation loss was 82 percent. After then, the VGGNet model was able to reach 95.32 percent accuracy in training, 71 percent accuracy in validation, and 73 percent loss in training..

5. Conclusion

Using information from a large group of actual patients, this study looks into the feasibility of making CRD forecasts. This extremely high accuracy of 99.0 percent will help in the early identification of renal illness. The proposed method uses an m-Xception-residual model in place of the Inception classification module used in mobile net. However, the proposed model uses a layer to extract classification features. A higher percentage of accurate forecasts is the direct outcome of these tweaks to the proposed model, which increase its accuracy. The optimal kernel size is determined by the SWO model. The results show that the recommended rate of 92% on the 30th epoch. Using the proposed models in public health initiatives has been shown to have positive benefits in our research. Future research of this kind will use supplementary data sets with additional data points from other demographics..

References

[1] Gulamali, F. F., Sawant, A. S., & Nadkarni, G. N. (2022). Machine learning for risk stratification in kidney disease. Current Opinion in Nephrology and Hypertension, 31(6), 548-552.

[2] Ventrella, P., Delgrossi, G., Ferrario, G., Righetti, M., &Masseroli, M. (2021). Supervised machine learning for the assessment of chronic kidney disease advancement. Computer Methods and Programs in Biomedicine, 209, 106329.

[3] Ebiaredoh-Mienye, S. A., Swart, T. G., Esenogho, E., &Mienye, I. D. (2022). A machine learning method with filter-based feature selection for improved prediction of chronic kidney disease. Bioengineering, 9(8), 350.

[4] Krishnamurthy, S., Ks, K., Dovgan, E., Luštrek, M., GradišekPiletič, B., Srinivasan, K., ... & Syed-Abdul, S. (2021, May). Machine learning prediction models for chronic kidney disease using national health insurance claim data in Taiwan. In Healthcare (Vol. 9, No. 5, p. 546). MDPI.

[5] Swain, D., Mehta, U., Bhatt, A., Patel, H., Patel, K., Mehta, D., ... & Manika, S. (2023). A Robust Chronic Kidney Disease Classifier Using Machine Learning. Electronics, 12(1), 212.

[6] Alsekait, D. M., Saleh, H., Gabralla, L. A., Alnowaiser, K., El-Sappagh, S., Sahal, R., & El-Rashidy, N. (2023). Toward Comprehensive Chronic Kidney Disease Prediction Based on Ensemble Deep Learning Models. Applied Sciences, 13(6), 3937.

[7] Venkatesan, V. K., Ramakrishna, M. T., Izonin, I., Tkachenko, R., &Havryliuk,

M. (2023). Efficient Data Preprocessing with Ensemble Machine Learning Technique for the Early Detection of Chronic Kidney Disease. Applied Sciences, 13(5), 2885.

[8] Venkatrao, K., &Kareemulla, S. (2023). HDLNET: A Hybrid Deep Learning Network Model with Intelligent iOt for Detection and Classification of Chronic Kidney Disease. IEEE Access.