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CNN-CatBoost ensemble deep learning model for enhanced disease detection and classification of kidney disease

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ABSTRACT

An efficient deep-learning prediction model for identifying chronic kidney disease (CKD) from exhaled breath is presented in this paper. The concentration of urea will be higher in CKD patients. Salivary urease breaks down the stored urea into ammonia, which is then excreted through breath. Thus, by monitoring the breath ammonia content, it is possible to identify the presence of high urea levels in the body. In this work, a novel sensing module is developed and applied to measure and assess the amount of ammonia in exhaled breath. Moreover, an effective deep learning prediction model that combines the CatBoost algorithm and convolutional neural network (CNN) is used to automate the prediction of disease. The proposed model, which combines the benefits of gradient-boosting and CNN, attained an exceptional accuracy of 98.37%. Experiments are conducted to evaluate the proposed model using real-time data and to assess how well it performs in comparison with existing deep learning methods. Our study's findings demonstrate that kidney disease can be accurately and noninvasively diagnosed using the proposed approach.

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1. INTRODUCTION

Kidney disease is the term used to describe damage to the kidneys that makes it difficult for them to filter wastes as efficiently as they should. Insufficient kidney function results in an accumulation of waste products and excess fluid in the circulation, leading to imbalances and toxins in the body [1]. Chronic kidney disease (CKD) develops over several months or years. A steady decline in kidney function is an indicator of end-stage renal disease, in which the kidneys completely fail and require dialysis or a kidney transplant to survive. Common causes of CKD include diabetes, hypertension, and glomerulonephritis. The signs and symptoms of kidney damage can include fatigue, edema, shortness of breath, nausea and confusion [2]. Depending on the type and severity of renal failure, there are a variety of treatment options available, including treating the underlying cause, changing one's diet, taking medication, and in severe cases, undergoing kidney replacement therapy [3]. Diagnosing CKD frequently involves a combination of laboratory testing, physical examination, and medical history. There are numerous biomarkers, or components that can be found in the blood or urine, that can be used to track the development of kidney disease. Blood urea nitrogen (BUN), or serum urea, is a major biomarker used in the assessment of renal disease and kidney function [4]. Urea is a waste product that is produced as the body breaks down proteins; the kidneys filter it out of the bloodstream so that it can be expelled in urine. A blood test is commonly used to check for kidney failure since it detects the amount of urea in the blood serum. The amount of urea in the blood indicates how well the kidneys filter. Elevated urea levels indicate impaired renal function.

Analysis of exhaled breath is a new subject of research in the areas of biomarkers and medical diagnostics. It may provide rapid, low-cost, non-invasive methods for diagnosing and monitoring a range of diseases, including several kidney-related conditions. While exhaled breath analysis has shown promise in the identification of certain respiratory and metabolic disorders, its potential as a direct biomarker for CKD is still under investigation. The gases, particles and volatile organic compounds (VOCs) that make up exhaled breath can reveal a multitude of information about a person's diet, metabolism, health and environmental exposure. VOCs in exhaled breath indicate metabolic activity and can function as biomarkers for certain illnesses [5]. We investigated the possibility of using breath ammonia as a biomarker for the diagnosis of CKD in our method. The breakdown of proteins and amino acids causes the body to release the gas ammonia. It is present in exhaled breath and can give details on renal and metabolic function. Ammonia builds up when kidney function is impaired in patients with CKD. The blood's ammonia levels will rise as a result. The relationship between breath ammonia and kidney disease has already been the subject of numerous investigations. However, only a few research have shown how to use breath samples to identify CKD [6].

According to the studies conducted by Bevc *et al.* [7] there is a linear correlation between breath ammonia, urea, and creatinine levels. Breath-based screening measures the amount of ammonia in exhaled breath to detect the presence of kidney disease. However, there isn't much ammonia gas released in the exhaled breath. As a result, it is challenging to measure the concentration of ammonia gas in breath samples without the use of extremely sensitive sensors. There aren't many tools or techniques for determining the amount of ammonia in breath. Krishnan *et al.* [8] reviewed the most modern analytical methods for detecting ammonia in exhaled breath. The existing laboratory-based testing methods are not suitable for rapid and precise diagnosis in real time since they require large detection devices and clinical procedures. Consequently, a rapid, non-invasive, accurate CKD diagnosis technique is needed. Therefore, in the proposed study, we built a detection apparatus based on a metal oxide semiconductor (MOS) sensor to measure the target biomarker from the exhaled breath [9].

In the healthcare sector, machine learning techniques are employed for automated prediction, development identification, and analysis of big, complex datasets. Convolutional neural networks (CNN) have virtually taken the role of classic machine learning approaches in many medical diagnostic applications in recent years. In the CNN learning network, the CNN itself handles both the feature extraction and the classification tasks [10]. This eliminates the need for an additional algorithm for feature extraction. CNN provides more dependable outcomes for automated disease identification than traditional learning methods. The use of innovative architectural principles and parameter optimization techniques has had a significant impact on CNN model development. Over the past few years, there has been a considerable advancement in CNN models [11]. Current research efforts are directed toward enhancing CNN architectures, investigating new methods for augmenting data and tackling interpretability and generalization issues across a range of demographics. To enhance classification performance, researchers have proposed hybrid networks that combine multiple learning models. CNNs with other neural network types or machine learning models combined into a hybrid network can provide several benefits depending on specific scenarios. This study presents the design and implementation of an effective CNN-CatBoost hybrid model that can provide automated predictions of diseases. CatBoost is an extremely effective gradient-boosting approach for classification-related applications [12].

2. METHOD

To identify the biomarkers and to make automated predictions of kidney disease, we have developed a novel medical detection system using CNN-CatBoost deep learning model. Figure 1 shows the block representation of the complete procedure. The entire system is composed of a deep-learning ensemble model for prediction and a gas sensing chamber. A sensor for measuring ammonia is integrated inside the breath analyzer chamber. We have also added a sensor to measure temperature and humidity, as these factors affect the ammonia estimation readings inside the gas chamber.

2.1. Detection model

A high concentration of ammonia in the blood and potentially in the breath can occur from the kidneys' inability to efficiently eliminate ammonia from the body when they are not operating at optimal capacity. To date, several techniques, such as chemical ionization, gas spectrometry and laser spectroscopy, have been developed for determining the concentration of different gases in exhaled breath [13]. The majority of developed instrumental methods are expensive, complicated and unsuitable for use in diagnostic settings. Although numerous sensor-based techniques, such as quartz crystal microbalance and chemical and optical sensors, have been developed, many of these are not suited for real-time application due to issues with detection limits or functioning in actual humidified breath samples. Numerous clinical trials have demonstrated that the electrochemical sensors utilized in recent studies are efficient [14]. In this work, we developed a new detection module to track the ammonia concentrations in exhaled breath. Over the commonly used blood test, the breath-based method suggested in this study offers numerous benefits due to its expedited and non-invasive nature.

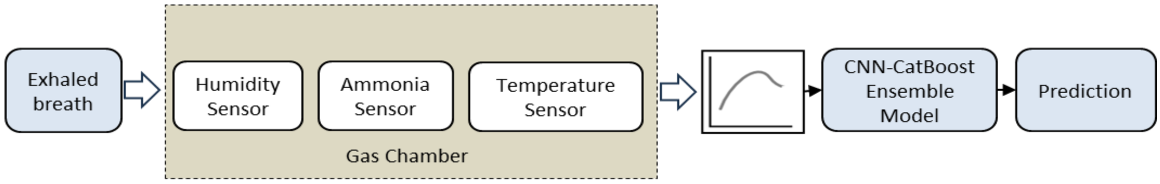


Figure 1. Block representation of the entire process

The schematic design of the breath analyzer detection chamber developed for the analysis is shown in Figure 2. The detection chamber has a mouthpiece for blowing the breath. A calibrated TGS 826 sensor is used to measure the amount of ammonia gas in the exhaled breath. The TGS 826 exhibits a change in electrical conductivity when exposed to ammonia gas. Tin dioxide (SnO2), a MOS material, and an integrated heating element make up the MOS gas sensor that is being employed [15]. The conductivity of the sensor varies when exposed to ammonia, and this variation is used to calculate the gas concentration. The TGS 826 sensor used here has a high sensitivity to ammonia gas, which allows it to detect the gas even in low concentrations. The sensing element is heated by an internal heating source within the sensor module. Ammonia detection requires this heating procedure in order to be accurate and consistent.

Figure 2. Schematic design of the detection chamber unit

The amount of free electrons in the sensing element changes as a result of interactions between the ammonia molecules and the metal oxide surface. The MOS material's electrical conductivity is impacted by this shift in electron concentration. To detect humidity and temperature, a DHT11 sensor is employed [16]. The sensor is calibrated by subjecting it to known concentrations of ammonia and monitoring variations in electrical resistance. With the help of the calibration curve, variations in the resistance of the sensor can be associated with ammonia concentrations. The conductivity of the sensor is directly proportional to the amount of ammonia gas produced inside the breath analyzer. An analog voltage is produced as a result of this change in conductivity. A microcontroller processing board is used to obtain the sensor's output response. An electrical circuit configuration is used to measure the electrical conductivity of the sensor element.

2.2. Deep learning prediction model

We developed a CNN-CatBoost deep learning hybrid model, which blends CNN with CatBoost, a gradient-boosting technique application, to generate predictions. This hybrid model performs better in predictions and can offer improved accuracy since it combines the benefits of CNN and CatBoost. Deep learning models find extensive use in applications related to pattern and image recognition. They are made up of several layers, including fully connected, pooling and convolutional layers. CNNs can be used for feature extraction since they automatically learn hierarchical representations of features from the input data [17].

The sensor's output signal is directly fed into the CNN as an input. The core of the CNN layout is the convolution layer. Using kernels, this layer extracts the important input features [18]. Two functions are involved in the mathematical process known as convolution. The result is the shifted and reversed form of the original function, which is obtained by multiplying one function by the other. The following equations describe how the kernel and the input are convoluted in CNN.

$$f(n) = s(n) * k(n) \tag{1}$$

$$f_i(n) = s(n)k(1) + s(n-1)k(2) + \dots + s(0)k(n) \tag{2}$$

$$f_i(n) = \sum_{l=-n}^{n} s(l+1)k(m-l+1) \tag{3}$$

where s represents the input signal, k represents the kernel, n and m represent the lengths of s and k, and f represents the output signal.

The features that CNN extracted are given to the CatBoost algorithm to perform the classification task in our work. Similar to other gradient-boosting methods, CatBoost constructs a sequence of decision trees. Every tree makes up for the mistakes made by the one before it, making the final prediction more accurate. CatBoost's inherent capacity to handle categorical features is one of its advantages. Since CatBoost can operate directly with categorical data, we don't need to explicitly preprocess categorical variables into numerical representations [19]. To avoid overfitting, CatBoost uses regularization techniques. Regularization improves the ability of the model to generalize to new data. Computational efficiency is a key design principle of CatBoost. On multicore computers, it facilitates parallel training, which speeds up the model training process. Furthermore, CatBoost will leverage GPU acceleration to expedite training. It can generate robust models that capture complex relationships in the data and perform better than many other techniques.

2.3. Samples and testing

The proposed sensing module was tested on 82 kidney patients and 102 healthy people. Prior to the testing phase, the fundamental testing procedures were followed. All participants received oral health instructions prior to the analysis. Before the test, the subjects were instructed not to eat, drink, smoke, or use mouthwash for a specific amount of time because these activities may introduce substances that could alter the accuracy of the results. The breath analyzer is calibrated before tests are administered to guarantee precise readings. Calibration involves adjusting the sensor readings in accordance with accepted standards to ascertain its accuracy. The participants are asked to blow into the breath analyzer through the mouthpiece section of the device. The user should continue to breathe evenly and continuously until the device indicates that a sufficient sample has been obtained.

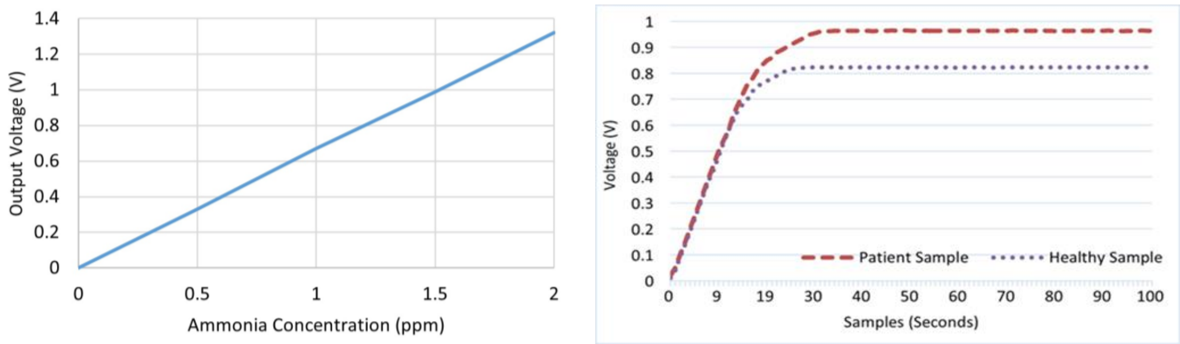
The ammonia in the exhaled breath reacts with the ammonia sensor inside the test instrument. The reaction produces an electrical current, and the magnitude of this current is proportional to the amount of ammonia in the breath. The amount of ammonia in the breath is directly correlated with the electrical current generated by the reaction. Using an Arduino board equipped with an ATmega328P controller, analog signals are obtained. MATLAB support packages for Arduino hardware are used to connect and communicate with the Arduino board. The analysis includes measurements of temperature, humidity, and voltage. We have incorporated a temperature and humidity sensor in the detection unit to account for the impacts of temperature and humidity. The sensor's raw signal is captured for 100 seconds and then sent directly into a trained deep-learning model to make the automatic prediction.

3. RESULTS AND DISCUSSION

Breath analysis holds great promise for clinical research and disease diagnosis while being a relatively new field of study. Medical research indicates that certain conditions or disorders change the makeup of the VOCs in the breath [20]. Breath samples can be automatically used to identify a variety of diseases thanks to advanced sensing methods and machine learning algorithms. The use of breath analysis for non-invasive kidney disease screening is addressed in this research. The objective of this research is to create personalized, quick, and affordable medical diagnostic tools that can be used to non-invasively identify CKD. The deep-learning technology for clinical diagnostics is explored in this work alongside a novel sensing methodology.

Since the detection unit we used is based on a novel methodology, it is required to evaluate the sensor's ability to identify kidney disease using an established technique for ammonia gas detection as shown in Figure 3. The detection range of the employed sensor is 1 to 10 ppm. To assess the sensor's responsiveness, it was initially subjected to a range of ammonia gas concentrations. Figure 3(a) displays the recorded voltage measurements for the different amounts of ammonia concentration. As the concentration of ammonia gas inside the breath analyzer chamber rises, the sensor's output voltage also rises. Healthy individuals usually have ammonia levels between 0.1 and 1.0 ppm. However, this concentration tends to increase in the breath of individuals with CKD because of the disturbance of the hepatic urea cycle. The degree of correlation between blood urea levels and exhaled breath ammonia was determined using Pearson's correlation analysis [21]. For these two parameters, a correlation coefficient of r=0.88 was attained. This indicates that the blood urea and breath ammonia values have a substantial positive correlation. A chemical analyzer was used to assess blood urea concentration, and our proposed detection module was used to monitor breath ammonia concentration for this analysis.

Voltage, humidity and temperature readings are among the test parameters measured in the analysis. The voltage output signal of the sensor for a healthy test sample and a kidney patient is displayed in Figure 3(b). This illustrates the relationship between rising ammonia concentrations and the sensor's voltage value. The output voltage of the sensor was lower in healthy samples than in disease cases. Temperature and humidity had no discernible effect on our test results because our testing was conducted in a controlled environment under normal operating conditions. By correctly calibrating the sensor signal, the impacts of humidity and temperature can be minimized.



(a) (b)

Figure 3. Sensor response (a) to changes in the concentration of ammonia gas and (b) voltage output signals for a patient case and a healthy test sample

The CNN model extracts the best features from the sensor signal. The test samples are then categorized using the integrated CatBoost classifier based on the selected features. For validation, a k-fold validation procedure is employed. In order to compare the performance of the proposed approach, we have designed and implemented the conventional deep learning models and evaluated them using the test samples. Conventional deep learning algorithms such as the Xception model, AlexNet, ResNet, DenseNet and MobileNetV2 are compared [22]. CNN along with the CatBoost classifier are used to build the proposed deep-learning network. A detailed performance comparison was conducted to examine the effectiveness of each of these models. The performance values that were achieved for each of these approaches are presented in Table 1.

Table 1. Comparison of the proposed model's performance values with those of the other deep learning models investigated in this study

Models	Accuracy (%)	Sensitivity	Specificity	Precision	F1 score	Miss rate
AlexNet	85.32	0.857	0.85	0.805	0.831	0.143
ResNet	85.87	0.85	0.865	0.829	0.839	0.15
DenseNet	90.76	0.911	0.904	0.878	0.894	0.089
MobileNetV2	93.48	0.937	0.933	0.915	0.926	0.063
EfficientNet	95.65	0.951	0.961	0.951	0.951	0.049
Xception	96.74	0.975	0.961	0.951	0.963	0.025
CNN-CatBoost	98.37	1	0.971	0.963	0.981	0

The Xception model produced the best accuracy of 96.74% when compared to all other conventional deep learning techniques analyzed in this study. Xception's primary architectural distinction is its utilization of depthwise separable convolutions. Since every filter in a typical convolution functions on every input channel, there are a lot of parameters involved. Pointwise and depthwise convolutions are the two distinct procedures that make up a depthwise separable convolution [23]. This lowers the computational complexity and parameter count. EfficientNet classified the samples with 95.65% accuracy. Compound scaling is used in this model, where the depth, width and resolution are all scaled at the same time. Conventional methods, on the other hand, only scale one of these elements. Inverted residuals, where the shortcut connections are between the narrow bottleneck layers, are a concept introduced by MobileNetV2 [24]. This structure facilitates better information flow and preserves low-dimensional embeddings. The samples were classified by AlexNet, ResNet, and DenseNet with 85.32%, 85.87% and 90.76% accuracy rates, respectively.

Compared to the other algorithms examined in this study, the CNN-CatBoost model achieved the highest accuracy of 98.37%. The proposed model's miss rate is zero, indicating that all instances of the positive class are correctly identified by the proposed model. Of the 184 samples evaluated, the proposed approach successfully identified 105 as healthy and 79 as kidney patients. A comparison of the error rates of different models is presented in Figure 4. The error rate indicates the frequency with which these models provide inaccurate results or forecasts that deviate from the actual values. It is an essential measure for determining a model's correctness and evaluating its performance. It is computed by finding the sum of false positive and negative cases and dividing it by the total number of predictions. The error rate of the proposed network is 0.016, which is quite low in comparison to all other approaches. To validate the test results, clinical validation is performed. We conducted the validation test with the assistance of medical experts, and the physicians verified the results. The outcomes of the clinical evaluation have almost exactly matched our test results. Only three samples had been missed by the proposed CNN-CatBoost model. All healthy case was correctly classified by the proposed model.

Receiver operating characteristic (ROC) curves for the proposed model and the Xception model are plotted to give a visual depiction of the connection between true positive rate and false positive rates. The ROC performance shows how well breath ammonia can determine whether a person has renal disease or not. The relationship between the true positive rate and false positive rate for various test set cut-off values is represented graphically by the ROC plot [25]. The ROC plot for the CNN-CatBoost and Xception models is shown in Figure 5. To check the accuracy of the analysis, the area under the curve (AUC) is computed from these plots. The best operating point for the model is determined by looking at the position on the ROC curve that maximizes the AUC. The AUC values obtained are 0.971 and 0.965 for the CNN-CatBoost and Xception classification models, respectively. This clearly shows the suggested model's superiority over the other traditional deep learning models.

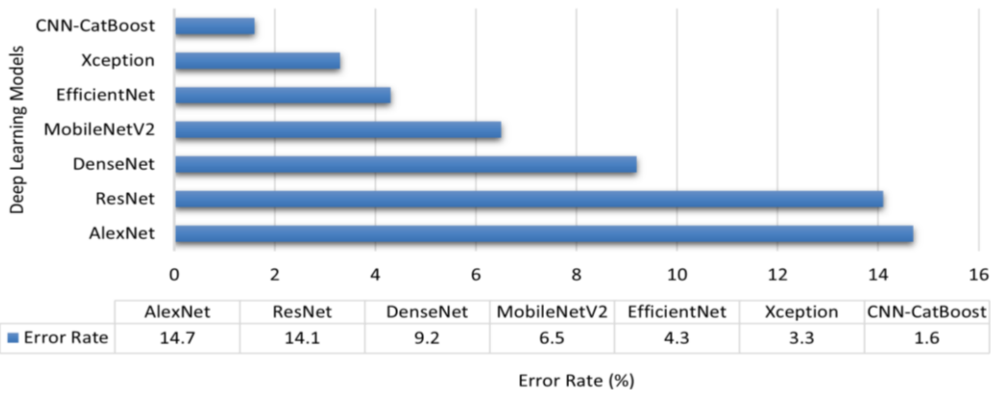


Figure 4. Comparison of error rates between various deep learning models

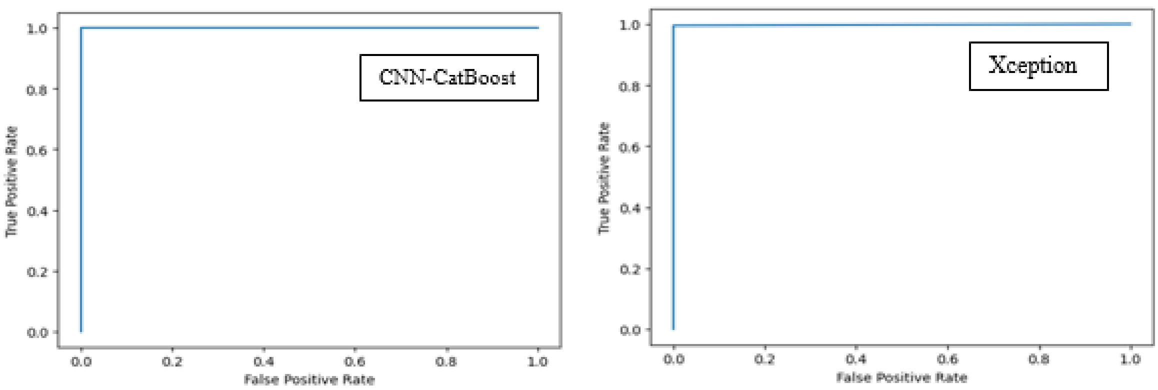


Figure 5. ROC curves obtained for testing samples for CNN-CatBoost and Xception models

4. CONCLUSION

In this work, a hybrid deep-learning model for improved kidney disease detection and classification has been developed by combining the CNN model and the CatBoost classifier. By combining CNN with CatBoost, model diversity is increased, which enables the ensemble model to identify and interpret a wider variety of patterns and correlations found in the sensor response signal. This work uses a novel sensor module that is designed to detect and measure the ammonia concentration in exhaled breath. To evaluate the proposed approach's discriminative ability to identify people with and without kidney disease, ROC and correlation analyses are performed. The statistical analysis shows that the proposed sensing method can be used as a non-invasive kidney disease detection method. To validate system performance, analysis metrics were compared with conventional deep-learning models. The Xception model had the highest classification accuracy of 96.74% among all conventional deep-learning approaches. Nevertheless, the proposed CNN-CatBoost model outperforms all other standard deep learning techniques, classifying the data with 98.37% accuracy. It is important to remember that breath-based CKD detection techniques are still in the early phases of research and development, despite these encouraging prospective benefits. To determine the validity, precision and clinical usefulness of these techniques in the diagnosis and follow-up of CKD, more research, clinical trials and validation are required.

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