International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A New Hybrid CNN-LSTM Model for the X-Ray Image-Based Detection of Paediatric Croup Cough Disease

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Submitted:22/03/2023 **Revised:**24/05/2023 **Accepted:**10/06/2023

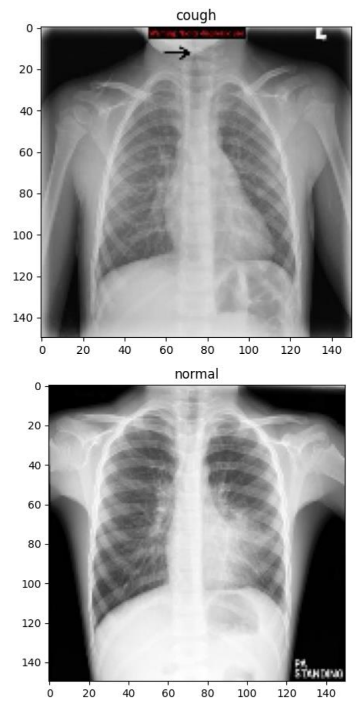
Abstract: The importance of computer-based illness detection has grown recently, especially in the medical field where radiological imaging methods like X-ray, CT, and MRI are essential for identifying a wide range of ailments. The development of the Coronavirus (COVID-19) has tested the limits of medical innovation. Due to the similarity in symptoms, it can be difficult for doctors to differentiate COVID-19 from respiratory diseases such croup, bronchitis, and laryngitis. The primary age range for children who contract croup is between six months and three years old. However, croup and COVID-19 symptoms frequently coincide. Due to the insufficient availability of pertinent information in medical pictures, x-ray-based croup detection is not frequently used, therefore an improved computer-based detection method offers a viable alternative for early diagnosis. In this context, we suggest a hybrid model for the categorization of croup cough that combines Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The LSTM is used for classification, whereas the CNN is used for feature extraction. Based on the experimental findings, the combined CNN-LSTM model, although being trained on a very short dataset, achieves an amazing testing accuracy of 97.66%.

Keywords: *COVID-19, CNN, pertinent, achieves, alternative, insufficient*

1. Introduction

A basic clinical examination, which includes evaluating the child's breathing and hearing for any unusual sounds, is often used to identify croup cough. A visual examination is also done to look for epiglottic or upper airway redness. An X-ray of an infected patient may show a distinctive pattern called the "steeple sign" below the vocal cords. This examination is helpful in identifying diseases like foreign body aspirations and others that are linked.

Epiglottitis, a disorder that needs prompt medical attention since it may be life-threatening, is another crucial factor associated to Covid-19. To determine the underlying source of obstruction in children with Covid-19, croup, or epiglottitis symptoms, a visual examination is necessary [1]. Radiographic results from X-rays or CT scans are extremely helpful to doctors in the early stages of diagnosis.



a. Cough b. Normal

Fig. 1 Croup and normal X-ray

The association between COVID-19, the infectious disease caused by the SARS-CoV-2 virus, and croup, a prevalent respiratory disorder in infants, was examined by Almendra et al. [2]. A typical infant X-ray scan and the croup cough are shown in Figure [1]. In the subglottic region of the larynx, a pronounced characteristic known as the "steeple sign" is present. For the subgroup, the most

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effective way to diagnose croup cough is by an X-ray-based visual examination.

The study by Guttmann et al. [3] focuses on the use of open radiography (X-rays) for newborns who present to the emergency department (ED) with respiratory infections. The study looks at how the usage of these radiographs varies and what effect access to paediatric care has on those variances. The study's conclusions shed light on the variables that affect the choice of whether to employ radiographic imaging in paediatric patients with respiratory problems in the emergency department.

The study team has used cutting-edge techniques to analyse X-ray images and find paediatric disorders. Several deep learning (DL) algorithms have recently been applied to the categorization and diagnosis of medical images. In the subject of intelligent healthcare, artificial intelligence is essential. When it comes to accurate categorization, DL models have regularly demonstrated promising outcomes. The detection of skin lesions, categorization of diabetic retinopathy, classification of pneumonia, and suppression of X-ray bone are notable applications of DL in medical imaging [4].

In order to classify croup cough using samples from paediatric X-rays, this study introduces a model that combines CNN and Long Short-Term Memory (LSTM). The suggested method uses LSTM to classify X-ray pictures and CNN to extract features from the input samples. The incorporation of LSTM is advantageous since it can efficiently learn from prior experiences by utilising the states of its long-term memory. The accuracy of the classification process is significantly improved by the combination of these two networks.

2. Literature Survey:

An overview of the various DL techniques used by researchers to categorise medical photographs is given in this review of the literature. It also examines contemporary methods that have been modified to diagnose the current COVID-19 pandemic utilising clinical pictures.

Feature extraction is an essential process in image processing and computer vision, as it involves removing valuable and distinctive characteristics from images to enable further analysis, recognition, or classification. In their study, Jiang et al. extensively investigated a wide range of techniques and algorithms for feature extraction in image processing and computer vision tasks. The efficiency and practical usefulness of these techniques in the area of image recognition were underlined by the authors. Chen et al. also suggested a novel method for bone suppression in chest radiography. To increase the visibility of non-bone tissues, notably lung tissue, their method employs cascaded convolutional networks in the wavelet domain. This technique aims to reduce the prominence of bone structures in the samples, thereby enhancing the visibility of other tissues, particularly lung tissue.

Rahimzadeh et al.'s study attempted to provide a mechanism for precisely categorising chest X-rays into COVID-19, Pneumonia, or Normal. The ResNet50V2 CNN and Xception architectures were used to build the model. 8,851 X-ray samples from normal cases, 6,054 X-ray samples from pneumonia cases, and 180 X-ray samples from COVID-19 cases made up the training dataset. Impressively, the model was able to properly identify cases of COVID-19 with an accuracy of 99.56% and a recall of 80.53%. A statistical parameter called recall assesses a model's capability to correctly identify each instance of a given class. In this situation, a recall of 80.53% means that the model accurately identified about 80% of the COVID-19 cases in the dataset.

Apostolopoulos et al. conducted a study on the classification of COVID-19 cases using 2D chest X-ray (CXR) images. In their investigation, they proposed a transfer learning (TL) based model that employed CNN. The model incorporated several contemporary CNN architectures, namely ResNet50V2, Xception, VGG19, MobileNet, and Inception. During model training, the dataset was divided using ten-fold cross-validation. Among the various models evaluated, VGG19 demonstrated the highest performance, achieving an accuracy of 93.48%.

A diagnosis system based on chest X-rays and utilising the VGG network with a small dataset was proposed by Horry et al. [9]. The technique used 322 samples of pneumonia cases and 115 samples of COVID-19 cases. A recall and precision rate of 80% was reached by the VGG19 and VGG16 classifiers, respectively.

In their study, Loey et al. presented a deep learning (DL) model built on the Generative Adversarial Network (GAN) architecture and using ResNet18, AlexNet, and GoogleNet as three transfer learning (TL) models. 69 x-ray samples of COVID-19 cases, 79 x-ray samples of bacterial pneumonia, 79 x-ray samples of viral pneumonia, and 79 samples of healthy cases made up the dataset used for this investigation. Among the TL models, GoogleNet demonstrated good performance in the multi-class case, achieving an accuracy of 80.6% for the four-class classification task. AlexNet surpassed other models with a stunning accuracy of 99.9% in the dual-class situation, while GoogleNet outperformed them with an accuracy of 85.2% in the tri-class scenario.

In [11], Singh et al. used Principal Component Analysis (PCA) to select features and VGG16 to diagnose COVID-19 using CT images with a 95.7% accuracy rate. In order to overcome the difficulties given by tiny datasets, Fong et al. [12] offered a case study on DL-based techniques, specifically employing Monte Carlo (CMC) and fuzzy rule induction. For the automatic identification and categorization of four distinct categories—confirmed cases, released cases, negative cases, and death cases—Bandyopadhyay et al. [13] presented a unique model utilising LSTM-GRU. The model's 87% accuracy in detecting affirmative cases was quite good.

Even with a small number of x-ray data, Khan et al. [14] developed a method that can detect COVID-19 utilising post-anterior CXR pictures using a DL network. The proposed model identified COVID-19 cases with an accuracy of 89.5%.

3. Methodology Proposed

We give an overview of CNN, LSTM, and the suggested model in this part, along with a thorough workflow. A DL method that combines CNN and LSTM networks uses CNN for feature extraction and LSTM to simulate the temporal correlations between data points for classification. By using this method, the model is able to recognise both regional and global trends in the data, producing predictions that are more accurate.

Dataset

There aren't many publicly accessible labelled croup cough datasets in well-known repositories since the croup cough condition is so uncommon. Because of this, only incomplete data samples from the Paediatric Pneumonia Chest X-ray images in the Kaggle repository were used in this investigation [15]. In place of a specific croup cough dataset that was unavailable, these data samples were used. 345 photos were used for training, 242 for testing, and 100 for validation in the dataset. Additional x-ray image samples were acquired from several medical image research websites and articles [16][17][18][19][20] to complement the sparse dataset for croup cough. These supplementary samples were obtained to enhance the dataset used in the study. The 108 data samples that were available weren't enough for a complete analysis, thus false croup x-ray samples were made using data augmentation techniques. 100 x-ray samples were used for testing and validation, while a total of 245 croup cough samples were used to train the model.

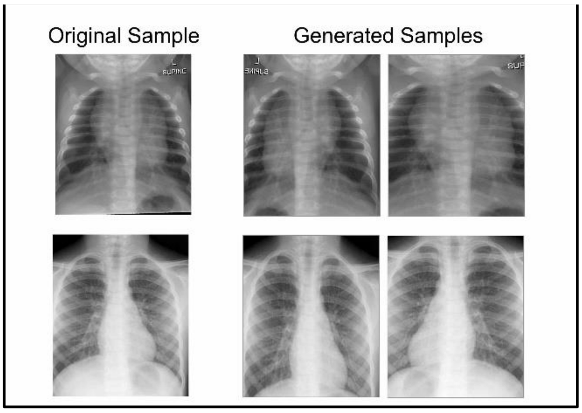

Fig. 2 Image Samples Produced Using GAN's

Through the process of GAN training, the image samples produced by Generative Adversarial Networks (GANs) are collected. A generator and a discriminator make up the two parts of the DL model known as a GAN. While the discriminator tries to tell the difference between actual and fake images, the generator creates synthetic ones. By accepting input from the discriminator during GAN training, the generator develops the ability to produce images that are more and more realistic. The generator becomes better at producing images that resemble the training dataset as the training goes on. The GAN-generated image samples are artificial reproductions that closely resemble genuine images. These samples are created using the characteristics and patterns that the GAN model has learned from the training dataset. Although they might not be actual images taken by cameras or scanners, they have qualities that are similar and can be applied in a variety of ways, such as data augmentation, artistic production, or study.

Model CNN-LSTM combined

A DL architecture that combines the advantages of CNN and LSTM networks is known as the combined CNN-LSTM model. With this suggested architecture, features will be extracted from input data samples using CNN, and LSTM will use those features to model the temporal connections between the data points. As a result, the model is able to properly represent both local patterns, such as edges and corners, and global patterns, such as objects and scenes, while also taking into account temporal relationships that span many time steps. The model can fully comprehend the data and produce precise predictions thanks to this integrated methodology.

The CNN is a crucial part of the model and is in charge of sifting through the input data to identify significant features. The CNN typically consists of several convolutional layers, each of which aims to capture a particular property present in the input data. This process results in a reduced-dimensional feature map that retains the most relevant information from the original input data.

The second part of the model, the LSTM, is responsible for modelling the temporal connections between the data points. The LSTM updates the hidden state at each time step using a set of weights and the feature maps obtained from the CNN as input. The information from earlier time steps is efficiently captured by this hidden state and transmitted to later time steps. Figure [3] gives a graphic explanation of the proposed hybrid network's architecture.

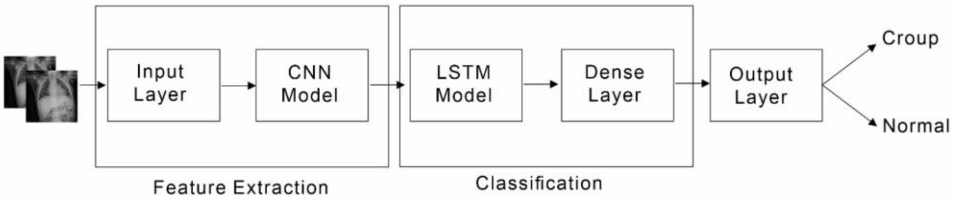

Fig. 3 Hybrid CNN-LSTM model proposed architecture

In order to effectively extract features from the input image frames, the proposed model employs two Conv2D layers. The first layer consists of 8 filters, while the second layer has 16 filters. To reduce the spatial dimensions of the output, a MaxPooling2D layer is incorporated. Additionally, a Dropout layer is included to mitigate overfitting. Finally, the output is transformed into a 1D vector using a Flatten layer.

The model has an LSTM layer after the earlier layers. This layer iteratively processes the feature vectors that the CNN layers have retrieved to capture temporal dependencies. In order to calculate classification scores for the target classes, a fully linked layer is then added. A sparse categorical cross-entropy loss function and RMSprop optimizer are used to train the model. The fit method is used during the training process to let the model learn from the data at hand and improve its performance.

CNN for Feature Extraction

The most popular method being used by many researchers in a variety of fields, such as object identification, image analysis, and picture classification [21, 22] is CNN-based feature extraction. The core idea behind CNN is to extract more complex and significant features from the input image by moving local significant characteristics from higher levels to lower layers.

Conv2D layers are crucial parts of CNN models. The input data is convolutioned with a set of learnable filters, commonly referred to as kernels or weights, within this layer. By moving these filters across the image in small steps known as strides, the input data is subjected to these filters. A dot-product between the filter and the area of the input data that overlaps is computed at each stage. In order to detect various features from the input data must be applied repeatedly.

The convolutional layer's output is known as the feature map. It reduces the depth of the incoming data while maintaining its spatial dimensions, which correlates to the number of filters used. Figure [4] presents an illustration of the CNN architecture.

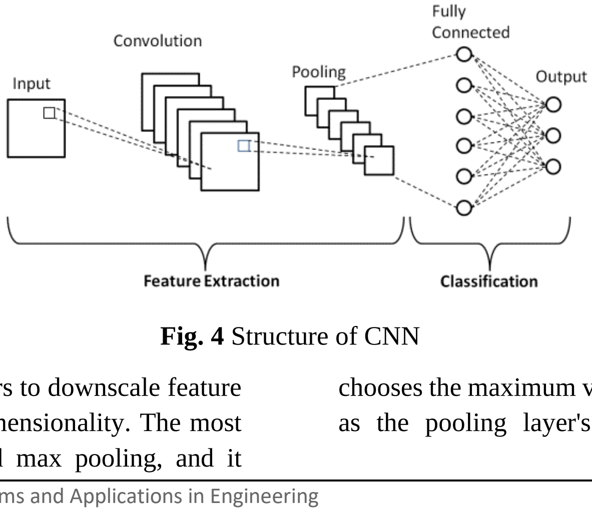

Fig. 4 Structure of CNN

CNNs frequently use pooling layers to downscale feature maps and thereby reduce their dimensionality. The most popular pooling method is called max pooling, and it chooses the maximum value found in each pooling region as the pooling layer's output. By removing the less significant features from the feature map, this method successfully keeps the most crucial ones.

Classifying using LSTM

Medical picture categorization tasks frequently use the Long Short-Term Memory (LSTM) architecture, a form of Recurrent Neural Network (RNN). It is especially well suited for modelling medical images because it is efficient at capturing long-term dependencies in sequential data, which are common in medical images that exhibit complicated temporal dynamics. Through the recognition of patterns that span numerous time steps, such as changes in a patient's condition over time, LSTMs allow models to make predictions that are more accurate. The model's capacity to recognise long-term dependencies in sequential data improves its prognostication skills. The model can more effectively comprehend and interpret temporal information in medical images because to this capability.

A hybrid CNN with LSTM architecture was used for tri-class classification utilising chest X-rays in the recent SARS-COVID-19 pandemic scenario [23]. Due to its ability to recognise temporal connections and patterns across many time steps, LSTMs must be incorporated into this design. By utilising their capacity to absorb and comprehend temporal information, LSTMs play a significant role in accurately identifying medical images.

The forget gate, input gate, and output gate are only a few of the gates that make up an LSTM network. Figure [4] depicts the LSTM's architectural layout. The new and prior cell states are designated as Ct and Ct-1, respectively, while the current input is shown as Xt. The symbols for the current output and the previous output are ht and ht-1, respectively.

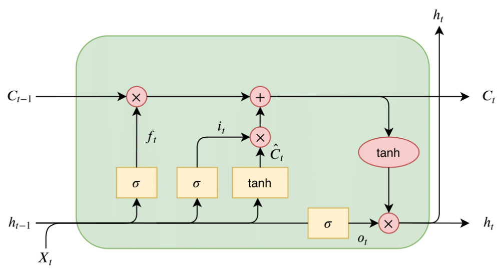

Fig 5. Architecture of LSTM

Metrics for evaluating performance

Using a well-known confusion matrix, the performance of the hybrid architecture for the classification problem of croup cough is assessed. This matrix provides a thorough examination of the model's predictions, enabling further study and a full evaluation of the model's performance.

Confusion matrix

The confusion matrix, a widely used assessment metric, is used to evaluate the performance of the suggested model. The true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) measurements are all included in this matrix. These measurements are essential to the computation of several performance metrics, including F1-score, recall, and accuracy.

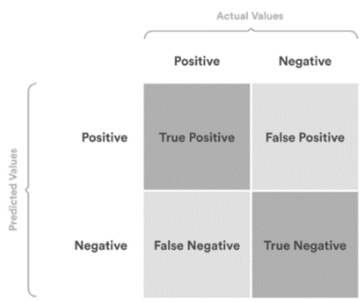

Fig 6 Confusion Matrix

Precision: (True Positive (TP)/ (True Positive (TP) + False Positive (FP)) [1]

Accuracy: (True Positive (TP) + True Negative (TN))/ (True Positive (TP) + False Positive (FP) + True Negative (TN) + False Negative (FN)) [2]

Specificity: (TN/ (TN+FP)) [3]

Sensitivity: (TP/ (TP+FN)) [4]

Recall = TP / (TP + FN) [5]

F1 Score = 2 * (Precision * Recall) / (Precision + Recall) [6]

4. Results and Discussion

The dataset is split into three distinct categories for the experiment: training, testing, and validation. The suggested method makes use of a seven-layer architecture and a learning rate of 0.0001 percent. Two convolutional layers, two pooling layers, one layer of flattening, an LSTM layer with a dropout parameter, and a dense layer for classification at the end make up this design. The dense layer makes use of the sigmoid activation function to solve the particular binary classification problem at hand. An examination of the traditional activation functions used in LSTM was done by Iqbal et al. [24]. The LSTM layer includes a dropout value to solve the issue of overfitting during training.

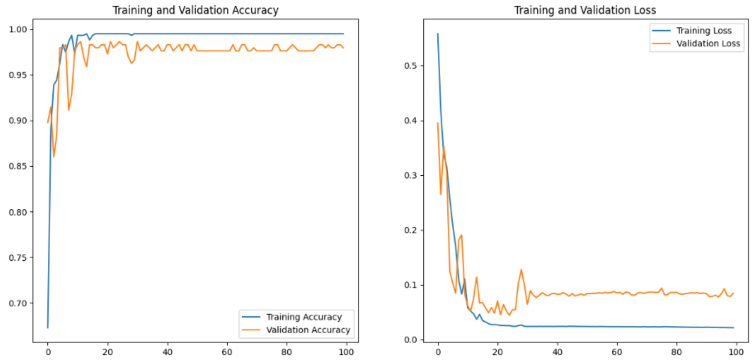

Fig 7. Training and Validation of Proposed Model Accuracy

The LSTM component in the studies had a batch size of 8 and was made up of 100 units. The proposed model has an accuracy of more than 94% throughout the first 10 epochs of the experiments. The number of epochs was then extended to 100 in order to guarantee the accuracy and durability of the model for the croup cough issue. The suggested architecture's combined CNN-LSTM model's training accuracy, validation accuracy, and loss are shown in Figure [7]. A gradual rise in the learning rate from 94.10% to 99.49% was visible. Notably, the experiment's validity accuracy and loss stayed positive the entire time.

	Cough	Normal
Cough	93	7
Normal	3	239

Table 2 Testing Dataset Confusion Matrix

Table [3] and Figure [8] present the experimental results. The outcomes show the CNN-LSTM network's promising classification accuracy. Additionally, the suggested model's confusion matrix shows that true positives (TP) and true negatives (TN) have higher values than false positives (FP) and false negatives (FN). The proposed model performs admirably in terms of a number of criteria, including sensitivity (96.48%), specificity (97.15%), and total accuracy (97.66%).

Measures	**CNN-LSTM**
F1 Score	95.31
recall	93.11
specificity	97.15
Sensitivity	96.88
Accuracy	97.66
Precision	97.31

Table 3. The projected CNN-LSTM network's performance

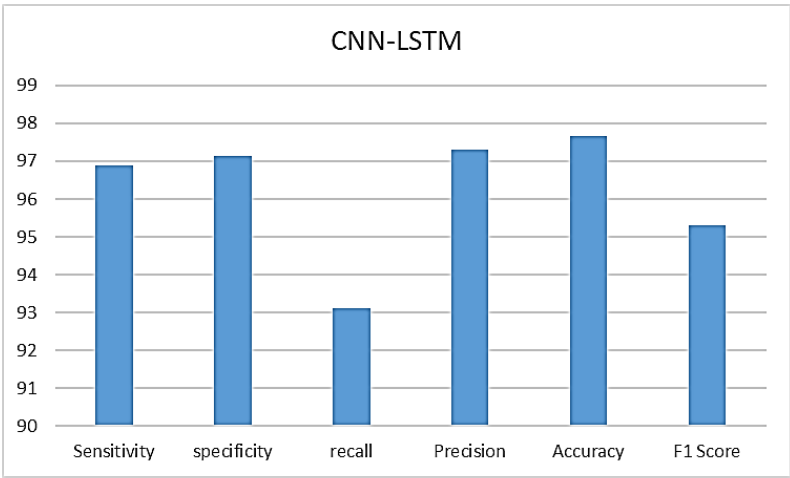

Fig 8 Metrics for the suggested model's performance

The results from the testing data are shown in the confusion matrix.

Based on the experimental results, the CNN and LSTM-based model shows considerable potential in detecting croup cough using x-ray images, achieving a promising level of accuracy. Emphasis was placed on accuracy as the primary performance metric to ensure that the proposed model successfully extracted the relevant features.

5. Conclusion

Due to the overlapping symptoms with other uncommon diseases like croup cough, there has been a considerable increase in the number of COVID-19 cases among newborns over the past two years, making it difficult for doctors to make a diagnosis. Using chest X-rays of newborns, a novel method combining deep CNN and LSTM has been proposed to detect croup cough. The suggested approach uses LSTM for classification and CNN for feature extraction. The suggested system's results are quite encouraging, with sensitivity, specificity, and accuracy ratings of 96.88%, 97.15%, and 97.66% respectively. These outstanding results show that the hybrid model is capable of correctly identifying paediatric croup cough from X-ray pictures. This development has the potential to greatly assist doctors in making precise and effective diagnosis in situations where differentiating between COVID-19 and croup cough becomes important.

Future Work

The small dataset size used in this study is one of its main limitations, which could have an impact on how well the experiments were ultimately completed. Future work will concentrate on collecting a higher number of data samples unique to croup cough in order to alleviate this constraint. To enable real-time performance evaluation, it is also crucial to compare the outcomes of the suggested model with assessments made by radiologists. This comparison analysis will shed important light on the model's functionality and suitability for use in clinical settings.

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