



IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 5, May 2022

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.165



9940 572 462



6381 907 438



ijircce@gmail.com



www.ijircce.com

Deep Learning based technique to detect COVID-19 using Cough Recordings

Priya Sharma A M¹, Rachana A C², Shrilatha K S³, Spoorthi M P⁴, Dr. Chandrika J⁵

UG Student, Department of IS&E, Malnad College of Engineering, Hassan, India^{1,2,3,4}

Head of the Department, Department of IS&E, Malnad College of Engineering, Hassan, India⁵.

ABSTRACT: COVID-19 disease has spread widely across the globe. Early diagnosis of COVID-19 infection is the need. The existing methods to detect disease is time consuming which can make impact on the rate of spreading. One of the symptoms of the disease includes coughing. The proposed approach uses cough recordings to classify the COVID-19 infected and non-infected person. The technique makes use of spectrogram of audio file to extract features like Mel-Frequency Cepstral Coefficients (MFCC), Spectral Centroid (SC), Spectral Bandwidth (SB), Zero Crossing Rate (ZCR), Chroma Frequencies (CF) and Spectral Roll-off. After extracting the features from spectrogram, the model stores the data into a .CSV file. Then, the model is trained using data to classify non-COVID-19 and COVID-19 infected patients. The proposed model achieved an accuracy of 94.74% on test data and the AUC-ROC value obtained by this model is 0.86.

KEYWORDS: COVID-19; Spectrogram; Mel-frequency Cepstral Coefficients; Accuracy;

I. INTRODUCTION

Coronavirus is an infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) which has hit the world severely. Symptoms of this include cough, fatigue, fever, headache, breathing difficulties, loss of smell and taste [1]. There is a high risk for older people to get infected by coronavirus due to their low immunity. The virus spreads through small liquid particles from the infected person when they sneeze, cough, sing, breathe or speak. Whoever come in contact with that person affected easily by COVID-19. The virus can also spread by touching eyes, nose or mouth after touching the surface of contaminated objects [2]. The solution to this problem is to identify the covid-19 infected person and put them in quarantine under medical assistance to stop further spreading of disease. The detection of COVID-19 infected person is commonly done by real-time Reverse Transcription Polymerase Chain Reaction (rRT-PCR), Transcription-Mediated Amplification (TMA), Reverse Transcription Loop-Mediated Isothermal Amplification (RT-LAMP) from nasopharyngeal swab [1].

Artificial Intelligence, Machine Learning and deep learning methods are extensively used to develop methods which can efficiently detect the disease. Deep learning models are used in analysis of Images. This, lead to the evolution of models which detect COVID-19 using Computed Tomography (CT) images. The same architectures were used to develop models which detects COVID-19 and Pneumonia using X-ray images. Since cough is one of the basic symptoms of COVID-19 [8], a new prospect of diagnosing the person based on cough is introduced, which is depicted in next section. The proposed method is a simple deep learning model which uses cough recordings as a dataset to detect covid and non-covid patients. The model is trained using various features of recordings to classify the dataset.

Section 2 summarises the literature review of related models. Section 3 depicts the proposed methodology. Section 4 discusses the experimental results of the work. Finally, Section 5 gives the concluding remarks of the work.

II. RELATED WORK

In [3], the author Wang Yunlu et al. proposed a model to classify screening of covid-19 infected people using various breathing patterns. The technique is to fill up the gap between training data and inadequate actual data from real world by considering the characteristics of breathing signals. The model used bidirectional neural networks like GRU network attentional tool to identify six different important respiratory patterns (Biots, Bradypnea, Cheyne-Stokes, Central-Apnea, Eupnea and Tachypnea). The precision, accuracy, recall and F1 of this model with respect to six distinct respiratory trends are 94.5%, 94.4%, 95.1% and 94.8% respectively. This model outperforms many existing models.

In [4] Imran Ali et al. implemented an artificial intelligence (AI) based screening approach to detect covid-19 through a mobile application. The mobile app is called AI4COVID-19 which records cough for three seconds and come back with a result within span of two minutes. Since cough is a basic symptom of more than thirty other medical

scenario, it makes difficult to diagnose covid through cough alone. Although, this model achieves an accuracy of 88.76%.

In [5] Hassan Abdelfatah et al. proposed a model using Recurrent Neural Network (RNN) to diagnose COVID positive. The model is evaluated based on auditory characteristics of patients' voice, breathing and cough using Long Short-Term Memory (LSTM). The use of RNN and Speech Signal Processing (SSP) had a major impact on early screening of COVID-19 virus. But this model had poor precision.

Jing Han et al. [6] proposed an intelligent analysis on covid-19 speech data. The technique considered four other parameters such as sleep quality, severity, anxiety and fatigue. The authors collected data from the apps which is launched by scientists and researchers from Cambridge university and Mellon university called "COVID-19 Sounds App" and "Corona Voice Detect App". The obtained dataset contains total of 378 segments after processing of data obtained from the above two Apps. Some of the sound pieces have been collected from 50 COVID-19 infected patients. The implemented model uses Support Vector Machine (SVM) by considering two acoustic features namely ComParE, eGeMAPS, where both feature sets achieved 69% accuracy.

Brown Chloe et al. proposed an android/iOS application to collect COVID-19 respiratory data from crowdsourced sounds of more than 200 positive cases and more than 7000 unique users. In [7] The authors considered three major parameters they are: i). COVID and non-COVID, ii). COVID positive with cough and non-COVID with cough, iii). COVID positive with cough and non-COVID asthma cough. For first parameter, the model achieved 80% of accuracy for 220 users with cough and breath. For second parameter, the model achieved 82% of accuracy for 29 users with cough only. For parameter 3, the model achieved 80% of accuracy for 18 users with breath only. The recall function of the model is slightly lower because of not specialized net to detect COVID-19.

In [8] Mohammed Bader et.al proposed a model which uses Mel-Frequency Cepstral Coefficients (MFCCs) and SSP (Speech Signal Processing) to extract samples from COVID and non-COVID. The dataset consists of three female and four male voices from healthy patients and two female, five male voices from COVID-19 infected patients. The infected patients' data is collected from zulekha hospital in Sharjah. Each patients' data consist of four times cough, voice counting the numbers from one to ten and four to five times of deep breath.

In [9] Chaudhari Gunavant et.al collected data from clinical environments, crowdsourcing and public media interview. The authors used the dataset to train machine learning model for COVID-19 detection. The AI algorithm correctly predicts COVID-19 infection with a 77.1% ROC-AUC (75.2-78.3%). This model can generalize to crowdsourced samples from Latin America and from South Asia.

In [10] LaguardaJord et.al proposed a model which can detect COVID symptoms from cough recordings. The dataset used was MIT open voice model (5320 subjects have recorded a healthy COVID-19 cough dataset). The model uses MFCC, ResNet50 classifiers to classify positive and negative cases with an accuracy of 97.1%, 96.7% and 79.2% from official test, doctor assessment and personal assessment respectively.

In [11] Kotra Venkata Sai Ritwik et al. collected small dataset from youtube videos to develop a model based on speech data. Support Vectors are used to represent each sentence of Mel filter bank features for each phoneme. The model successfully classifies COVID positive patients with the non-COVID patients and achieved 88.66% accuracy and 92.7% F1-Score.

III. PROPOSED METHODOLOGY

A. Collection of Data

The first step is to collect the data. The data is collected from crowdsourcing where it contains a total of 170 recordings. The dataset contains both COVID-19 infected and non-infected persons' cough recordings. After collecting the dataset, the model extracts the spectrogram for each and every audio file using librosa library of python [13]. Spectrogram is a visual representation of frequencies of a signal with time. A signal of an audio file is variation of air pressure. Figure 1 and 2 shows the wave form of the signal which can be analyzed by computer software. Fourier transforms allows to convert the signal from time domain to frequency domain, The result is known as spectrum. Spectrogram visually represents signal's loudness/amplitude, as it varies over time at different frequencies. Figure 3 and 4 shows spectrogram for non-COVID and COVID-19 infected cough recordings.

B. Extracting Features from Spectrogram

After all the audio files get converted into respective spectrogram, the proposed model extracts Mel-Frequency Cepstral Coefficients(MFCC), Spectral Centroid(SC), Spectral Bandwidth(SB), Zero Crossing Rate(ZCR), Chroma Frequencies(CF) and Spectral Roll-off.

- Mel-Frequency Cepstral Coefficients: Mel Frequency Cepstrum is a representation of short-term power spectrum of sound. MFCCs are coefficients that make up MFC which is commonly used in speech recognition and music retrieval information.

- Spectral centroid: As the name suggests, it is one of the parameters used in digital signal processing where the location of centre of mass of the spectrum is present. It has robust connection with brightness of the sound [17].
- Spectral Bandwidth: Bandwidth is the range of frequencies. The sum of maximum deviation of signal on either side of the centroid is called as Spectral bandwidth at that time frame [14].
- Zero Crossing rate: ZCR denotes the number of times signal changes its value from positive to negative and vice-versa, which is then divided by total length of the frame. It is excessively used in music information retrieval and speech recognition [5].
- Chroma Frequencies: It is a tool used to analyze music or speech whose pitches are categorized into 12 different pitch classes [16].
- Spectral Roll-off: It is the frequency below which a specified percentage of the total spectral energy lies. It used to distinguish between harmonic (below roll-off) and noisy sounds (above roll-off) [5].

C. Writing the data to .csv file

After extracting all the features, values are stored and saved in a file with .csv extension. All the values represent different features and can be easily analysed and pre-processed.

D. Analysing the data

In this step, pandas library of python is used to pre-process the data. The target values are encoded so that 0 represents non-COVID and 1 represents COVID positive data. The values are normalized/rescaled to maintain a balanced distribution, where mean value is 0 and standard deviation is 1. After that the data is split into train data (67%) and test data (33%).

E. Building the Network

Using Keras, a simple neural network architecture is built with an input layer, 4 hidden layers with relu activation function and an output layer with 2 neurons to classify two different classes. The model is then compiled with Adam optimizer. Adam optimizer is generally better because of its faster computation time and requires only few parameters for tuning. Loss function used is sparse categorical entropy since the model deals with labels which are integer values [17]. The model is trained with 100 epochs. During each epoch, Keras displays the number of instances processed so far, loss and accuracy of training data.

IV. RESULTS

The model is evaluated using accuracy and AU-ROC metrics. Accuracy on the test data resulted in 94.74%. Figure 5 shows the train accuracy of the model and Figure 6 shows the plot of loss function against epochs. AU-ROC (Area Under the Receiver Operating Characteristics) Curve can be a better representation of how the model is performing. Figure 7 illustrates the AU-ROC Curve of the proposed model. AUC results for our dataset attain higher than 0.86 which indicates, the model is capable of distinguishing between the two classes.

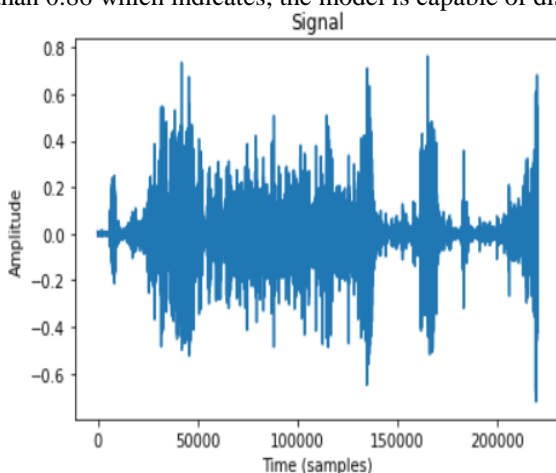


Fig. 1 Waveform of non-COVID cough

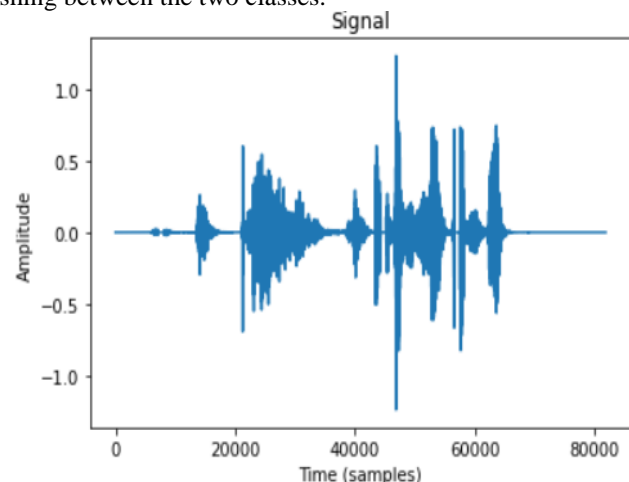


Fig. 2 Waveform of COVID-19 infected cough

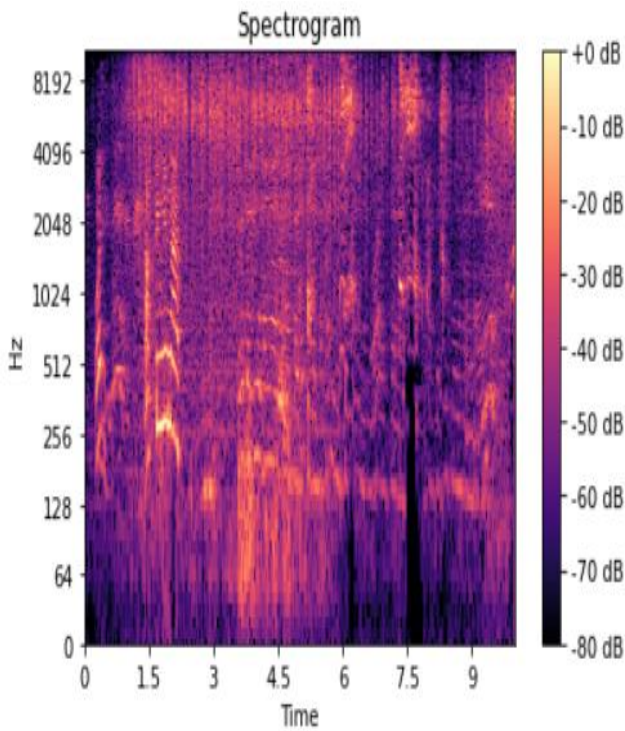


Fig.3 Spectrogram of non-COVID cough

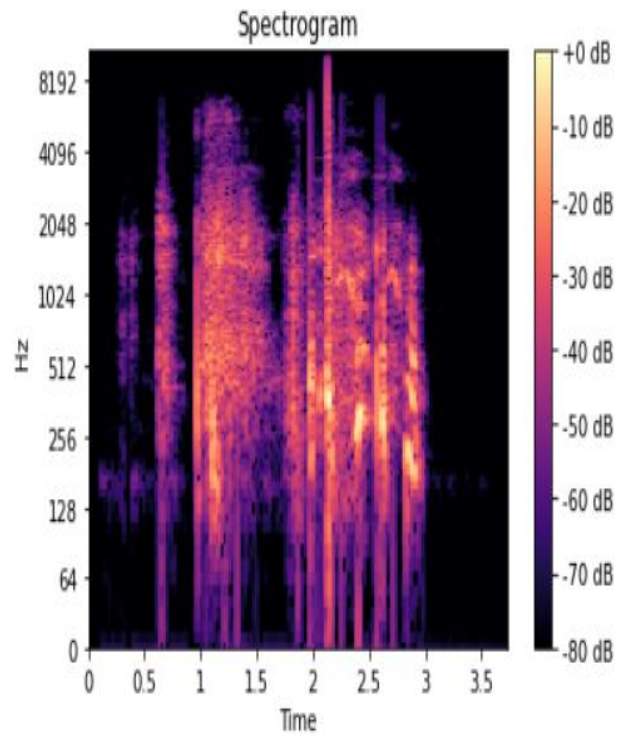


Fig.4 Spectrogram of COVID-19 infected cough

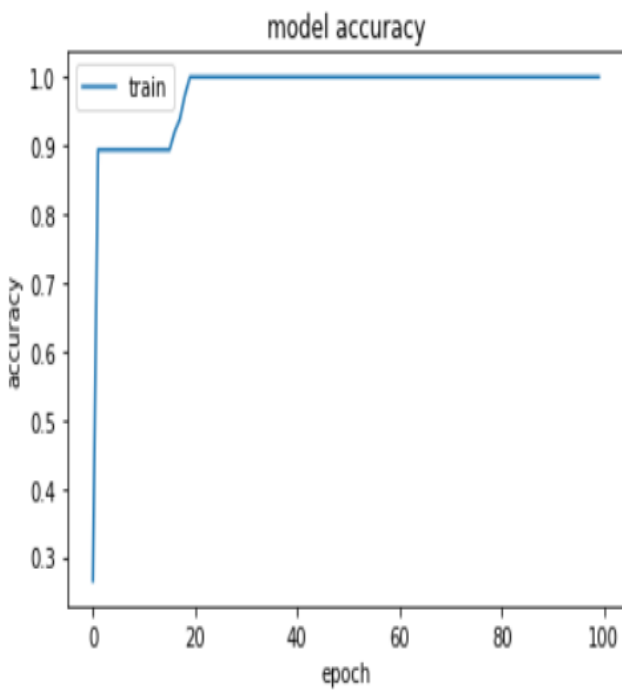


Fig.5 Accuracy of the model

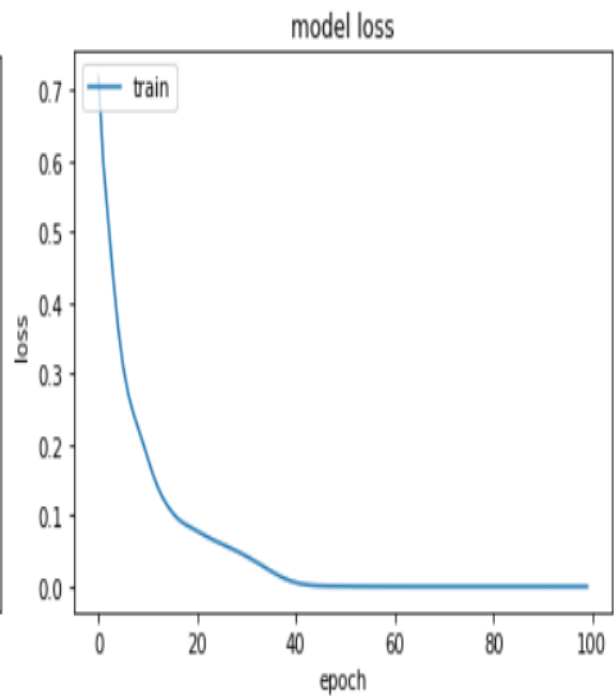


Fig.6 Loss function against epochs

Model: auROC=0.865

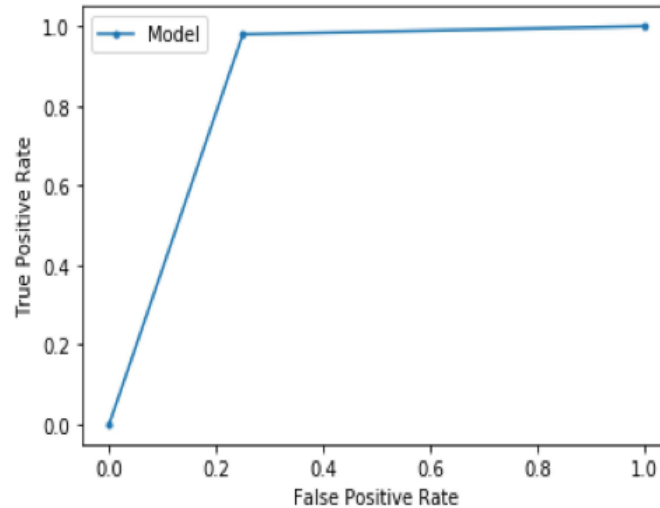


Fig. 7 AUC-ROC Curve

V. CONCLUSION AND FUTURE WORK

This study demonstrated a robust model which can classify the cough recordings into non-COVID and COVID-19 infected classes. The model exploits different acoustic features of recording to train the model achieves 0.86 AUC-ROC value and accuracy of 94.74%. Since the proposed model is inexpensive, simple and easily deployable, it has some potential to decrease the load on other medical and health care institutions.

The limitation is mis-diagnosis of class. Cough is one of the symptoms of many other diseases [18]. Therefore, further analysis is necessary to distinguish COVID-19 and other respiratory disorders.

REFERENCES

1. "Covid-19", <https://en.m.wikipedia.org/wiki/COVID-19>
2. "Coronavirus disease (COVID-19): How is it transmitted?", WHO news-room Questions, <https://www.who.int/news-room/questions-and-answers/item/coronavirus-disease-covid-19-how-is-it-transmitted>
3. Wang Y, Hu M, Li Q, et al. (2020) Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner. arXiv: 2002.05534.
4. Imran A, Posokhova I, Qureshi HN, et al. (2020) AI4COVID-19: AI-enabled preliminary diagnosis for COVID-19 from cough samples via an app. DOI: 10.1016/j.imu.2020.100378.
5. Hassan A, Shahin I, Alsabek MB (2020) Covid-19 detection system using recurrent neural networks. DOI: 10.1109/CCCI49893.2020.9256562.
6. Han J, Qian K, Song M, et al. (2020) An early study on intelligent analysis of speech under covid-19: Severity, sleep quality, fatigue, and anxiety. arXiv: 2005.00096. DOI: 10.21437/Interspeech.2020-2223.
7. Brown C, Chauhan J, Grammenos A, et al. (2020) Exploring automatic diagnosis of covid-19 from crowdsourced respiratory sound data. DOI: 10.1145/3394486.3412865.
8. Bader M, Shahin I, Hassan A (2020) Studying the similarity of COVID-19 sounds based on correlation analysis of MFCC. arXiv: 2010.08770. DOI: 10.1109/CCCI49893.2020.9256700.
9. Chaudhari G, Jiang X, Fakhry A, et al. (2020) Virufy: Global applicability of crowdsourced and clinical datasets for AI detection of COVID-19 from cough. arXiv: 2011.13320.
10. Laguarda J, Hueto F, Subirana B (2020) COVID-19 artificial intelligence diagnosis using only cough recordings. DOI: 10.1109/OJEMB.2020.3026928.
11. Ritwik KVS, Kalluri SB, Vijayasenan D (2020) COVID-19 patient detection from telephone quality speech data. arXiv: 2011.04299
12. Melek, M. Diagnosis of COVID-19 and non-COVID-19 patients by classifying only a single cough sound. *Neural Comput&Applic* 33, 17621–17632 (2021). <https://doi.org/10.1007/s00521-021-06346-3>

13. B. McFee et al., "librosa: Audio and Music Signal Analysis in Python," Proc. 14th Python Sci. Conf., pp. 18-24, 2015, doi:10.25080/Majora-7b98e3ed-003
14. Pramono, Renard & Imtiaz, Anas & Rodriguez-Villegas, Esther. (2019). Automatic Cough Detection in Acoustic Signal using Spectral Features. Conference proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Conference. 2019. 7153-7156. 10.1109/EMBC.2019.8857792.
15. Hall JI, Lozano M, Estrada-Petrocelli L, Birring S, Turner R. The present and future of cough counting tools. *J Thorac Dis.* 2020;12(9):5207-5223. doi:10.21037/jtd-2020-icc-003
16. Shah, Ayush&Kattel, Manasi & Nepal, Araju& Shrestha, D. (2019). Chroma Feature Extraction.
17. Cross Entropy vs. Sparse Cross Entropy: When to use one over the other; <https://stats.stackexchange.com/questions/326065/cross-entropy-vs-sparse-cross-entropy-when-to-use-one-over-the-other>.
18. K. K. Sahu, A. K. Mishra, K. Martin, and I. Chastain, "COVID-19 and clinical mimics. Correct diagnosis is the key to appropriate therapy," *Monaldi Arch. Chest Dis.*, vol. 90, no. 2, Art. no. 2, May 2020, doi: 10.4081/monaldi 2020.1327.

BIOGRAPHY

Dr. CHANDRIKA J is presently working as Professor and Head of the Department, Information Science & Engineering, at Malnad College of Engineering, Hassan. Her area of interests includes Big Data analytics, Software Engineering and Distributed data processing. She has more than 40 publications in International Conferences and peer reviewed journals.



INNO  SPACE
SJIF Scientific Journal Impact Factor

Impact Factor: 8.165

 **doi**[®]
cross **ref**

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  ijircce@gmail.com



www.ijircce.com

Scan to save the contact details