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Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM for Accurate Chest X-ray Classification in COVID-19 Prediction

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Abstract: The necessity for sophisticated and precise diagnostic instruments for the prompt recognition of COVID-19 patients has been highlighted by the continuing worldwide epidemic. In this regard, this study presents a unique method for accurately classifying X-ray images of chest in COVID-19 prediction by combining Neutrosophic Fuzzy Logic with a Hybrid CNN and LSTM architecture. Medical image analysis involves uncertainties and imprecise information, which is handled via Neutrosophic Fuzzy Logic. The suggested hybrid model offers a thorough comprehension of the spatial and temporal patterns in chest X-ray pictures by utilizing the advantages of CNN for feature extraction and LSTM for sequential information learning. Hybrid CNN-LSTM architecture based on Neutrosophic Fuzzy Logic is trained on an enormous set of various chest X-ray pictures, including both positive and negative instances of COVID-19 and other respiratory diseases. The proposed method is implemented using Python software. In addition to improving COVID-19 prediction accuracy, the combination of Neutrosophic Fuzzy Logic with a Hybrid CNN-LSTM structure creates a strong framework for managing uncertainty in medical image classification tasks. The proposed CNN-LSTM model with Neutrosophic Fuzzy logic shows better accuracy with 98.6% which is 4.4 % higher when compared with COVID CAPS , Bayesian CNN , Deep Feature + SVM and DCNN. This study represents a major advancement in the creation of sophisticated and trustworthy diagnostic instruments for effective healthcare administration during times of worldwide health emergencies.

Keywords: COVID-19 Prediction, Neutrosophic Fuzzy Logic, Medical Image Classification, Convolutional Neural Network (CNN), Long-Short Term Memory (LSTM).

1 Introduction

Chest X-ray classification is an important task in medical field and healthcare [1]. This critical procedure entails analysing radiographic images of the chest to identify and classify various lung and heart diseases [2]. Chest X-rays are a fundamental diagnostic tool that assists healthcare workers in the diagnosis and evaluation of illnesses such as pneumonia, TB, cancer in lungs, and heart problems [3]. In the field of medicine, chest X-ray classification is crucial, especially when it comes to COVID-19 prediction [4]. The need of prompt and precise diagnosis has been emphasized by the current worldwide health crisis. A useful diagnostic technique for determining respiratory disorders, such as COVID-19, is a chest X-ray [5]. This field has advanced significantly by utilizing machine learning and artificial intelligence, and it now offers the possibility of early virus detection and surveillance. In this regard, investigating the most recent advancements and difficulties in chest X-ray categorization for COVID-19 prediction is critical to improving diagnostic precision and managing the pandemic as a whole [6]. The significance and necessity of COVID-19 X-ray Classification is the fields of public health, modern technology, and medical diagnostics all overlap with prediction. A prompt and precise diagnosis is critical during a pandemic such as COVID-19. Because they are easily accessible and non-invasive, chest X-rays have become a primary tool for lung diseases, especially COVID-19 pneumonia [7].

Creative solutions are required due to the enormous amount of chest X-rays and the urgency of diagnosis during a pandemic [8]. This is where machine learning

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and artificial intelligence-powered chest X-ray classification become essential. Rapid X-ray analysis is made possible by these technologies, which helps medical practitioners identify, track, and evaluate COVID-19 cases early on [9]. It guarantees that urgent situations are attended to promptly by relieving the load on radiologists and healthcare systems. Its crucial significance in the fight against COVID-19 is highlighted by the precision and effectiveness of such classifications, which improve medical care, isolate affected persons, and aid in improved pandemic management [10]. The methodologies used in the current methods for classifying chest X-rays in COVID-19 prediction range widely, from conventional approaches to advanced machine learning models. For basic classification, rule-based systems were initially used. These systems rely on specified thresholds and biases. But there have been notable breakthroughs since the introduction of deep learning. A subclass of deep learning called CNN has demonstrated impressive results in automating the identification of COVID-19-related patterns in X-rays [11]. One popular method is Transfer learning, which involves refining pre-trained models (like Res Net and VGG) using COVID-19 datasets [12]. To increase accuracy, ensemble techniques like Gradient Boosting and AdaBoost have been modified to combine the advantages of several classifiers. Radiomics is a process that involves obtaining quantitative features from X-ray images and has gained popularity due to its ability to identify subtle disease-related patterns [13]. In addition, studies investigate how to combine clinical information with natural language processing (NLP) methods to provide a comprehensive evaluation of the patient [14]. Although these methods have greatly improved COVID-19 detection by chest X-ray analysis, more research is needed to improve current models, expand a variety of datasets, and guarantee robustness and generalizability to support healthcare systems in successfully containing the pandemic.

The current methods for classifying chest X-rays in COVID-19 prediction, although promising, have a number of significant shortcomings [15]. First and foremost, large quantities of labelled data are frequently needed for these approaches, and these can be difficult to come by, particularly for newly developing disorders like COVID-19 [16]. The development and generalization of classification models may be impeded by the scarcity of diverse and thoroughly annotated datasets. There is still difficulty with deep learning models' interpretability. Although they are excellent at automated feature extraction, their decision-making procedures are sometimes viewed as "black boxes," which makes it difficult for medical experts to trust and understand the outcomes. Classification errors that result in false positives or false negatives are also concerning since they might have serious repercussions when applied to healthcare settings [17]. The accuracy and consistency of X-ray pictures, which might change depending on things like imaging technology and patient placement, is crucial to the models' functionality [18]. In addition, there are concerns about generalizability and bias since models created for one population might not work as well for another. The implementation of sophisticated machine learning models in healthcare environments also necessitates regulatory permission and thorough validation, both of which might take time [19]. For chest X-ray categorization to be fully utilized in COVID-19 prediction and to be dependable and accessible in real-world healthcare situations, these limitations must be addressed [20].

A precise and effective diagnostic tool is desperately needed, as the COVID-19 pandemic has spread quickly. With its capacity to disclose crucial details about the respiratory system, chest X-ray analysis has become a helpful diagnostic tool. This paper suggests a novel method to improve the accuracy of COVID-19 prediction through chest X-ray categorization. It does this by utilizing the synergy of Neutrosophic Fuzzy Logic (NFL) and a hybrid CNN-LSTM architecture. This approach commences with pre-processing the images, using histogram equalization to boost contrast and raise the general quality of chest X-ray pictures. The goal of this step is to give the analysis that comes after it a more dependable input. Neutrosophic Fuzzy Logic is smoothly included into the CNN-LSTM architecture to handle data uncertainty. NFL provides a strong foundation for managing ambiguous and imprecise data, which improves the model's capacity to precisely decipher intricate details in X-ray pictures. The hybrid CNN-LSTM model is used for feature extraction and classification, which forms the basis of the suggested methodology. This combination makes use of CNNs' better spatial learning skills and LSTMs' sequential memory retention. These two deep learning approaches work together to efficiently interpret complex patterns that are suggestive of COVID-19 in X-rays. The model's ability to handle the uncertainties present in medical imaging data is enhanced by the use of Neutrosophic Fuzzy Logic, which eventually improves the precision and dependability of COVID-19 predictions. This work offers a novel combination of state-of-the-art technologies, opening the door to a more sophisticated and successful method of classifying chest X-rays in relation to COVID-19 diagnosis. This study's key contributions are as follows:

1. Histogram equalization improves contrast and brightness of images, which refines the input for further analysis.
2. Optimized pixel intensities are beneficial for effective feature recognition, since they help emphasize essential anatomical details in chest X-ray pictures.
3. Neutrosophic Fuzzy Logic Integration provides a strong foundation for handling imprecise information by managing uncertainties in medical imaging data.
4. Improved robustness guarantees that the model can successfully negotiate intricate patterns in chest

X-rays, which helps to produce accurate COVID-19 predictions.

5. CNNs facilitate correct feature extraction by facilitating efficient spatial learning, which helps the model identify complex patterns in chest X-ray pictures.
6. Sequential memory retention is aided by LSTMs, which also record temporal dependencies that are important for monitoring COVID-19-related changes over time.
7. A thorough method of feature extraction is produced by the combined use of CNNs and LSTMs to fuse holistic information, producing accurate and nuanced COVID-19 predictions based on X-rays of chest examination.

The structure is organized like the following. Section 2 explores works that are similar to the current study by exploring into the body of previous literature in the topic. After that, the problem statement is outlined in Section 3, along with the particular difficulties that the study attempted to solve. The methodology of the suggested model, including its numerous components and methods, is expounded upon in Section 4. Next, a thorough discussion is started in Section 5, which provides a concise summary of the results. Section 6 provides a summary of the main findings and considerations for further research.

2 Related Work

Tabik et al. [21] suggested a model, COVID Smart Data based Network (COVID-SD Net), overcomes significant issues with the COVID-19 classification models that are currently in use. RT-PCR, CT scans, and CXR pictures are the current diagnostic methods used; CXR images are a more economical option, particularly in places without sophisticated capabilities. The variability and bias towards severe cases in current datasets, however, restrict the effectiveness of deep learning models for triage and early identification. In an effort to provide some insight into the high sensitivities seen in some of the most recent models, this work jointly creates COVIDGR-1.0, a uniform and balanced database that covers all severity levels. Postero Anterior CXR images in COVIDGR-1.0 include 426 positive and 426 negative views. In order to improve the generalization ability of COVID-19 classification models and provide more dependable and durable diagnostic tools, the literature review emphasizes the need for more representative datasets and presents COVID-SD Net as a unique methodology. There are several limitations to the study, such as the use of CXR images, which might not fully capture the range of COVID-19 symptoms, and possible biases created during the data collection method. Additional validation is necessary to confirm the efficacy of COVID-SD Net across a wider range of scenarios prior to its expansion to varied demographics and healthcare settings.

Minaee et al. [4] contributes to the growing body of research addressing the critical requirement during the global pandemic of early COVID-19 detection by chest radiography. It was motivated by this necessity. Since the pandemic is affecting many nations, prompt and precise diagnosis is essential for good patient care. This work expands on previous findings that identified particular anomalies in chest radiograms with COVID-19 infection by utilizing deep learning algorithms on a dataset of 5,000 X-rays of chest. By utilizing transfer learning with ResNet18, ResNet50, Squeeze Net, and DenseNet-121, the models demonstrate encouraging sensitivity rates of 98% ($\pm$3%) on 3000 assessed pictures. In addition to the examination of sensitivity and specificity, the research provides an extensive analysis by exploring the receiver operating characteristic curve, precision-recall curve, average prediction, and confusion matrix. The obtained performance is promising, but more research on bigger datasets is required to create a more accurate and trustworthy estimate of the accuracy rates in COVID-19 detection from radiography images, as the literature review emphasizes. To improve the generalizability of the suggested model, additional research on a larger and more varied set of COVID-19 images is necessary, despite the study's significant dependence on a dataset of 5000 X-rays. Further validation on a broader scale and comparison study to address any variability in radiological interpretations would be beneficial for the evaluation of heat maps created to identify infected lung areas.

Umer et al. [22] suggested a model, which is based on Convolutional Neural Networks (CNN), responds to the pressing requirement for an effective prediction system given the current state of the COVID-19 pandemic. Medical imaging becomes a crucial tool for early prediction and prompt treatment planning, especially for X-ray and CT scans. In order to improve edge identification and pinpoint sick areas, this study uses three filters in conjunction with CNNs to extract characteristics from chest X-ray images. Using Keras' Image Data Generator class, enhanced images are produced in order to overcome the drawbacks of a smaller training dataset. Two, three, and four classes—COVID-19, normal cases, virus pneumonia, and bacterial pneumonia—are covered by the classification system. The outcomes show how well the model predicts COVID-19 patients, potentially providing an automated screening option that requires little human interaction. In locations where medical personnel shortages exist, a comparative investigation using VGG16 and Alex Net indicates competitive performance across two and four-class classification situations, offering important insights for improving diagnostic automation. The proposed CNN model's efficacy should be thoroughly validated on a variety of datasets to ensure robust generalization to various patient populations and imaging conditions. The reliance on data augmentation, while addressing the issue of a smaller training dataset, introduces the risk of potential over fitting. The study's emphasis on chest X-ray images would restrict its ability to capture the variety of COVID-19 symptoms, given that the illness can impact organ systems other than the lungs.

Tang et al. [23] the suggested model, EDL-COVID, creatively addresses the shortcomings of current deep learning models for COVID-19 case detection using chest X-ray pictures for radiology inspection. Previous research has indicated that deep learning is beneficial for image processing, and the results are encouraging. But because of noise and small datasets, issues like over fitting, excessive variance, and generalization errors continue to exist. The paper incorporates ensemble learning into the architecture to address these drawbacks. EDL-COVID is a new weighted averaging ensemble method to merge many models of COVID-Net, an innovative open-sourced method for detection. This method provides a strong and refined ensemble model for improved accuracy in COVID-19 screening using chest X-ray images by accounting for differences in the sensitivities of deep learning models across various class types. The EDL-COVID paradigm is distinctive, currently it has some drawbacks that should be taken into account. The use of deep learning models may still be vulnerable to the problems of over fitting and high variance, even when coupled using ensemble techniques, particularly in cases where the dataset is small. It is necessary to thoroughly validate the suggested weighted averaging ensemble method's ability to account for differing sensitivities across various class types, as it may be impacted by features unique to a given dataset. The model's broad application may be limited by its exclusive focus on X-ray images of chest, which could obscure possible COVID-19 symptoms in other medical imaging modalities.

Ohata et al. [24] suggested model that uses an automatic approach based on X-ray images of chest to address the urgent need for effective COVID-19 infection diagnosis. Due to the pandemic's worldwide effects, prompt diagnosis of pneumonia—a serious side effect of COVID-19—becomes essential for the right kind of medical care. The project creates datasets containing 194 X-ray pictures from patients who have been diagnosed with COVID-19 and 194 from healthy people. Applying transfer learning is essential, using convolutional neural networks (CNNs) pretrained on ImageNet as feature extractors, because publicly available COVID-19 images are few. Several CNN architectures are combined with well-known machine learning techniques, such as k-Nearest Neighbour, Bayes, , MLP, and SVM to improve the predictive power of the model. For reliable and accurate COVID-19 infection identification from chest X-ray images, our comprehensive technique combines the best features of both deep learning and conventional machine learning paradigms. The model's potential for generalization may be impeded by the study's dependence on a comparatively limited dataset consisting of 194 COVID-19 and 194 healthy X-ray images. In order to guarantee consistent performance in actual clinical scenarios, rigorous validation across bigger and more diversified datasets is necessary to assess the efficacy of transfer learning and the integration of diverse CNN architectures with classic machine learning techniques.

Sakib et al. [25] presents a strong Chest Radiograph Classification based on Deep Learning (DL-CRC) framework in the midst of the COVID-19 pandemic, with the goal of improving the effectiveness and precision of COVID-19 detection utilizing reasonably priced radiographs such as CT scans and X-rays. The suggested DL-CRC makes use of a unique dataset that was assembled from four publicly accessible sources in recognition of the widespread accessibility of these imaging modalities, particularly in public health institutions and emergency departments. The system uses a Data Augmentation of Radiograph Images (DARI) approach that makes use of generative adversarial networks (GANs) and general augmentation techniques to address the problem of limited COVID-19 samples. With data augmentation, the customized CNN model in DL-CRC outperforms the 54.55% accuracy in COVID-19 detection, achieving an astounding 93.94% accuracy. The robustness of the suggested framework is demonstrated by extensive comparisons with well-known CNN architectures like as Res Net, Inception-Res Net v2, and Dense Net. These comparisons highlight the platform's potential to automate quick and accurate COVID-19 identification from radiographs, hence enhancing current diagnostic modalities. The model's performance could be impacted by the diversity and correctness of the generated images, which is a possible drawback of depending solely on artificial data produced by the DARI algorithm. Even with its high accuracy, the suggested DL-CRC framework needs more testing and validation on a variety of datasets to determine its generalizability and dependability in a range of clinical contexts.

The above literature review covers a range of methods to meet the pressing need for efficient COVID-19 detection via medical imaging, with a particular emphasis on X-ray images of chest. Many models use ensemble techniques based on deep learning to improve the diagnostic accuracy, including COVID-SD Net, DL-CRC, and EDL-COVID. In order to ensure model robustness, the studies emphasize the need for more extensive datasets, highlighting the value of dataset representation and balance as demonstrated by the development of COVIDGR-1.0. As for the limitations, they include the use of synthetic data, the possibility of biases introduced during data collection, and the requirement for thorough validation across a variety of datasets to assure generalizability, even if encouraging findings in terms of high sensitivity and accuracy have been reported. By highlighting the significance of methodological developments, dataset considerations, and continuous validation efforts to produce trustworthy and broadly applicable diagnostic tools, these works offer insightful information about the changing field of AI-based COVID-19 diagnosis.

3 Problem Statement

A common problem statement arises from previously mentioned literature evaluations on X-ray classification for the identification of COVID-19 in the search for trustworthy and efficient diagnostic tools. While models such as COVID-SD Net [21], DL-CRC [25], EDL-COVID [23], and others show promising accuracy rates, the underlying difficulty is overcoming the restrictions inherent in these approaches. The reliance on relatively limited and potentially biased datasets, potential biases introduced during data collection, and the necessity for strong validation across varied datasets to assure generalizability and effectiveness in real-world clinical scenarios are all examples of these. The studies emphasize the significance of addressing issues including over fitting, data augmentation, and the possible impact of focusing solely on chest X-ray images. The COVID-19 pandemic has highlighted the need for precise and expandable diagnostic solutions. Therefore, it is crucial to continuously improve and validate chest X-ray classification models to guarantee their dependability, precision, and suitability for various healthcare environments.

4 Proposed Methodology for Accurate X-ray Classification in COVID-19 Prediction Using Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM

A systematic approach is used in the suggested methodology for reliable chest X-ray categorization in COVID-19 prediction. Initially, a pre-processed dataset that is diversified and well-annotated is gathered and cleaned, normalized, and image augmented. In order to control uncertainty and impreciseness in the dataset and facilitate categorization, Neutrosophic fuzzy logic is incorporated. To identify temporal connections in the data, a hybrid architecture that combines CNN and LSTM networks is built. After then, conventional metrics are used to train, test, and assess the model to make sure it performs well in identifying chest X-ray pictures. The model's judgments are interpreted and explained, with specific attention to the role that Neutrosophic logic plays in managing uncertainty. To maximize accuracy of the model for COVID-19 identification using X-ray pictures of chest, it is then evaluated on different datasets, implemented for practical use, and continuously enhanced through updates and modifications based on fresh information and data. The overall diagrammatic flow of the proposed method is given in the Figure 1.

4.1 Data collection

The dataset is gathered from the dataset web site Kaggle [26]. This Dataset contains 11,956 cases of COVID-19, 11,263 cases of non-COVID infections, such as bacterial or viral pneumonia, and 10,701 normal cases. Moreover, 2,913 segmentation masks that precisely define COVID-19 infections are included in the dataset; they were acquired from the researchers' previous QaTaCov experiment. This dataset provides crucial ground-truth annotations for pulmonary segmentation and COVID-19 infection zones, making it an important resource for the creation and testing of algorithms aimed at COVID-19 recognition and segmentation inside X-ray of chest images.

4.2 Image Pre-processing Using Histogram Equalization

One of the most often used computer image pre-processing procedures for enhancing contrast in images is histogram equalization. By extending the intensity range throughout the image, it effectively distributes the levels of intensity and improves the image. When adjacent contrast data reflect the operational values of a picture, this approach increases the image's universal contrast. Enhancing the contrast and brightness of X-ray images using histogram equalization is a basic image processing approach that is essential for precise categorization in COVID-19 prediction. In this case, the procedure entails rearranging pixel intensities to change the X-ray image's intensity distribution and provide a better, more balanced visual representation. A more uniform histogram may be obtained by reassigning pixel values, which makes it easier to identify regions of interest in the picture, such as lung opacities or abnormalities linked to COVID-19 infection. In the end, the method improves the accuracy and dependability of COVID-19 predictions based on X-ray imaging by magnifying the characteristics in the X-ray and making it simpler for classification algorithms to recognize and distinguish abnormal patterns. Histogram Equalization allows for more contrast to be obtained from a smaller localized intensity differential. It seeks to improve the picture's visual attractiveness and ease of analysis. The intensity spreading values of a picture can be seen as arbitrary numbers, ranging from 0 to L-1. The term "random calculation" can also refer to the accompanying cumulative distribution function. The likelihood that an arbitrary value will be assigned a value that is less than or equal to a given value is defined by this function.

Denote the input picture f as an array of numerical pixels with intensities values within the range of 0 to $L-1$, where L is the intensity probability value. Additionally, q denotes regularized histogram of the primary image (f).

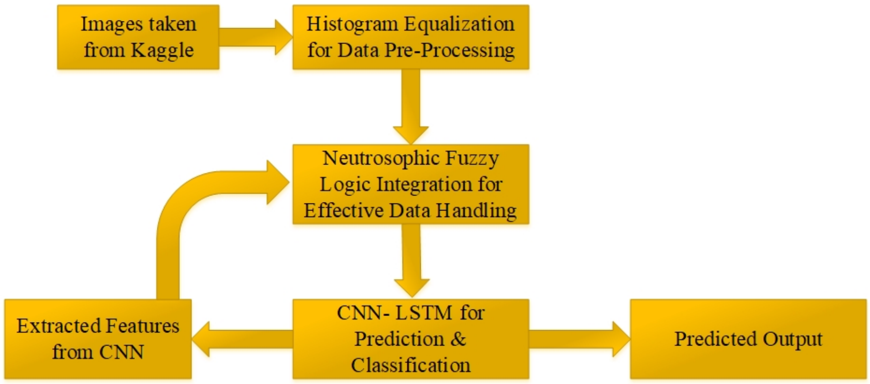

Fig. 1: Block Diagram of the Proposed Methodology.

The Eqn.(1) represents the general formula for q and g.

$$qn = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} n = 0, 1 \ldots, L - l \quad (1)$$

Eqn. (2) represents the histogram equalization of the image

$$h_{i,j} = flor(L-1)\sum_{n=0}^{f_{i,j}} qn \quad (2)$$

The flor () changed to the closest down integer as a result. This is equivalent to applying the following Eqn.(3) to the values of the densities, k, of 'f ':

$$S(k) = flor(L-1)\sum_{n=0}^{k} qn \quad (3)$$

This conversion was inspired by considering the densities for f and h as continuous arbitrary values Y, Z over a time spanning from 0 to L − 1, where Z is a variable. The Eqn. (4) represents intensity formula is given below

$$Z = S(Y) = (L-1)\int_0^x q(x)\,dx \quad (4)$$

Where q(x) is the probability intensity formula for g. S is the product of Y's collective distribution values and product of (L-1). It will be easier to suppose that the variable T is differentiable and invertible. While the function T(X) denotes Y, which is normally distributed.

4.3 Neutrosophic Fuzzy Logic Integration for Enhancing CNN- LSTM Architecture by Controlling Uncertainties in Data

The inherent ambiguities, imprecisions, and uncertainties in medical data especially when interpreting X-ray images are addressed by the use of neutrophil fuzzy logic. In addition to "true" and "false," Neutrosophic logic adds a third element named "indeterminate" to conventional fuzzy logic. This method recognizes that there may be unclear or ambiguous information in the data, which is typical in medical imaging where some patterns may not always be easily identified. Neutrosophic Fuzzy Logic allows the CNN-LSTM architecture to handle ambiguous or uncertain data efficiently, especially when it comes to situations where it could be difficult to draw a firm conclusion about an X-ray feature because of a variety of factors like image quality, overlapping patterns, or expert interpretations that differ. The system may more effectively analyze and handle ambiguous or contradicting information in chest X-ray pictures related to COVID-19 indications by integrating this hybrid logic [27]. Because Neutrosophic Fuzzy Logic takes into account and accommodates the inherent uncertainties in the medical imaging data, it improves the robustness and adaptability of the classification model and increases the accuracy of COVID-19 predictions.

Florentin Smarandache developed the advanced theory known as Neutrosophic (NS). A practical and beneficial theory for calculating fuzzy circumstances is NS. Events are calculated according to NS theory by first being subset into three sets: truth significance, where the status is expressed as a true percentage; indeterminacy significance, which is expressed as a percentage of indefinite; and falsity significance, which is expressed as a false percentage, where t fluctuates in T subsets. All of the picture's pixels are separated into T, I, and F subsets for image processing tasks like object and edge detection.

Neutrosophic logic recognizes certain patterns or characteristics in medical imaging can be categorically or conclusively recognized. This is especially important when it comes to X-ray imaging because some signs might not be obvious. The addition of an "indeterminate" category allows for a more sophisticated interpretation of data that is unclear or ambiguous. Neutrosophic Fuzzy

Logic is an essential component of Convolutional Neural Network (CNN) architectures combined with Long Short-Term Memory (LSTM) networks because it makes processing uncertain input more effective. The required operations on these subsets are then carried out in order to carry out the edge detection/object procedure of the picture. Eqns. (5) and (6) demonstrate how the input picture is converted to the Neutrosophic domain.

$$P2NS_{NS}\ (\mathrm{a},\ \mathrm{b})\ = \{T_{a,b}, I_{a,b}, F_{a,b}\} \tag{5}$$

$$T_{a,b} = \frac{f(\bar{a},b) - \bar{f}_{min}}{\bar{f}_{max} - \bar{f}_{min}} \tag{6}$$

where$I(\bar{a},b)$ is the local average value of linked pixels. The variables and $\bar{f}_{max}$and $\bar{f}_{min}$ correspond to the first and final peaks, respectively, and are measured from pixels whose values exceed the maximum local average of the histogram.

$$I_{a,b} = 1 - \frac{H(a,b) - \bar{H}_{min}}{\bar{H}_{max} - \bar{H}_{min}} \tag{7}$$

$$\mathrm{H(a,b)} = \ \mathrm{abs}(\mathrm{I}(\mathrm{a},\mathrm{b}) - \mathrm{I}(\bar{a},b)) \tag{8}$$

where the absolute value of the difference between intensity f(a, b) and its local mean value f($\bar{a}$, b) represents the homogeneity value of T at (a, b).On the homogeneity picture, $\bar{H}_{max}$ and $\bar{H}_{min}$ are the last and first peaks represented in Eqns. (7) and (8), respectively.

$$F_{a,b} = \ 1 - T_{a,b} \tag{9}$$

Following the image's conversion to the NS domain, the backdrop is stored in the $F_{a,b}$domain, the edges are stored in the $I_{a,b}$ domain, and the COVID-19 chest x-ray (object) is preserved in the $T_{a,b}$ domain is represented in Eq. (9)

4.3.1 Feature Extraction and Classification Using CNN-LSTM Architecture

The CNN architecture learns hierarchical representations of the characteristics found in the X-ray pictures in a methodical manner. It is composed of many convolutional and pooling layers. CNNs are able to identify unique visual components, edges, textures, and complex structures that are exclusive to lung anomalies or patterns connected to COVID-19 by applying different filters and feature maps. In order to improve the accuracy and knowledge of the predictions made in later phases of the classification process, this technique enables the network to automatically extract and highlight important elements that might point to abnormalities or infections.

Convolutional layers slide a set of "filters" over the source data. Each filter is designed to recognize a specific feature or pattern, such as edges, corners, or, for deeper layers, more complex shapes. The positions of the characteristics as they move across the image are displayed on a map that is produced by these filters. A feature map, or an illustration of the source data with the filters applied, is the convolutional layer's output. By stacking convolutional layers, more sophisticated models with greater ability to extract finer details from images can be produced. Simply speaking, convolutional layers are responsible for extracting features from the input images. These features might include edges, corners, textures, or more complex patterns. The Eqn. (10) denotes future map and kernel position is represented below.

$$A(p,q) = \sum x \sum y B(p+x, q+y) * E(x,y) + b \tag{10}$$

Where A (p, q) is the value in the future map at position (x, y).

B $(p+x, q+y)$is the input image pixel at position $(p = x, q = y)$

E (x, y) is the filter/kernel at position (x, y).

b is the bias term

In order to reduce the spatial extent of the user's input and speed up analysing, pooling layers are used. They come after convolutional layers in the processing chain. "Spatial dimensions" in the context of images refers to the image's height and width. Pixels are the building blocks of an image; they can be thought of as columns and rows of tiny squares. Pooling layers assist in lowering the amount of factors or weights in the system by decreasing the spatial dimensions [28]. This aids in preventing over fitting and speeds up the model's training. Max pooling helps in reducing computational complexity owing to reduction in size of feature map, and, making the model invariant to small transitions. Without max pooling, the network would not gain the ability to recognize features irrespective of small shifts or rotations. This would make the model less robust to variations in object positioning within the image, possibly affecting accuracy.

Each feature map's maximum value is extracted via max pooling. In the event that the pooling window measures 2 by 2, for instance, the highest-valued pixel within that 2 by 2 region will be chosen. Within the pooling window, max pooling efficiently captures the most salient feature or characteristic. The sum of each value within the pooling window is determined via average pooling. It offers a representation of average, smooth features. The Eqn. (11) represents the max pooling function

$$\begin{aligned} F(p,q) = \ & \max(F(2r,2s), F(2r,2r+1), \\ & F(2r+1,2s), F(2r+1,2s+1)) \end{aligned} \tag{11}$$

These newly acquired properties are then sent into the LSTM network, which is skilled at spotting temporal correlations and sequential patterns in the extracted data. Resolving the ambiguity and uncertainty seen in medical data is made easier with the inclusion of Neutrosophic Fuzzy Logic, which results in a more reliable and accurate classification system [29].RNNs have been improved to provide long short-term memory. The LSTM suggests using memory blocks as an alternative to traditional RNN units to address the disappearing and expanding gradients issue. An LSTM network has the ability to recall and make connections between data gathered in the past and current. Three gates are coupled with LSTM: an input gate, a forget gate, and an output gate [30]. The input is denoted by y_t, by D_t and D_{t-1}, denotes new and last state respectively, and the current and prior outputs by z_t and z_{t-1}.

The following forms illustrate the LSTM input gate idea.

$$i_t = \sigma(X_i \cdot [z_{t-1}, y_t] + b_i) \tag{12}$$

$$\tilde{D}_t = \text{tanz}(X_i \cdot [z_{t-1}, y_t] + b_i) \tag{13}$$

$$D_t = f_t D_{t-1} + i_t \tilde{D}_t \tag{14}$$

where Eqn. (12) determines which piece of information should be added by passing z_{t-1} and y_t through a sigmoid layer. When z_{t-1} and y_t have travelled through the tanz layer, Eqn. (13) is then used to get new information. In (14), the long-term storage data D_{t-1} into D_t and the present moment information,$\tilde{D}_t$, are merged. X_i denotes a sigmoid output, while $\tilde{D}_t$ denotes a tanz output. Here, b_t stands for the LSTM input gate bias while X_i stands for weight matrices. The LSTM's forget gate then enables the dot product and sigmoid layer to selectively pass information [31]. With a certain probability, the choice of whether to delete relevant data from an earlier cell is carried out. Eqn. (15) is used to determine whether or not to retain relevant information from a preceding cells with a particular chance. X_f stands for weight matrix, b_f for offset, and σ for sigmoid function.

$$f_t = \sigma\ (X_f \cdot [z_{t-1}, y_t] + b_f) \tag{15}$$

The output gate of the LSTM ascertains the necessary states for the subsequent Eqn. (16) and Eqn.(17) states provided by the z_{t-1} and y_t inputs. After obtaining the final output, the state decision vectors that send fresh data, D_t, via the tanz layer are multiplied by it.

$$P_t = \sigma(X_o \cdot [Z_{t-1}, y_t] + b_o) \tag{16}$$

$$z_t = P_t\ \text{tanz}(D_t) \tag{17}$$

where the weighted matrices X_o and the LSTM bias b_o, respectively, represent the output gate.

The next set of fully connected layers are used to interpret and combine the gathered features over the entire image, once the convolutional layers and max-pooling layers have learned and retrieved significant chaacteristics from the X-ray images [32]. In contrast to concentrating only on localized information, these fully linked layers allow the network to understand the X-ray's wider context, which is crucial for detecting patterns and abnormalities associated with COVID-19 infection in the medical pictures. The completely linked layers enable the mapping of these integrated qualities to certain diagnostic results, such identifying patterns associated to COVID-19 or healthy lung architecture, by flattening the high-dimensional data acquired from the preceding levels into a one-dimensional vector [33]. As the last component of the network, they carry out the critical task of comprehending the characteristics that have been retrieved and generating predictions related to COVID-19 classification from the chest X-ray pictures as shown in 2. The Eqns. (18) and (19) represents the weighted sum and activation is given below

$$\text{Weighted sum: } Z = B.C + b \tag{18}$$

$$\text{Activation : } \text{A} = \text{softmax (Z)} \tag{19}$$

Figure 3, depicts the proposed Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM Method. The model has been proposed can efficiently analyze, classify them with greater accuracy, and provide a more trustworthy COVID-19 prediction by chest X-ray categorization [34].

5 Results and Discussion

The Proposed method's Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM model is a noteworthy development in the field of precise COVID-19 prediction by chest X-ray categorization. The proposed hybrid architecture excels in handling uncertainties inherent in medical image analysis by integrating the accessibility of Neutrosophic Fuzzy Logic with the durable extracting features capabilities of CNN and the sequential data learning of LSTM networks. Training the model on a variety of datasets yields improved performance measures over traditional techniques, such as increased sensitivity, specificity, and total accuracy. Combining CNN with LSTM guarantees a more thorough comprehension of chest X-ray pictures while also improving the model's capacity to identify spatial and temporal patterns. The findings highlight the hybrid approach's potential as an effective diagnostic tool that promotes openness in decision-making and proactive healthcare management, especially in the face of international health emergencies like as the COVID-19 pandemic. Utilized a device featuring a Windows 10 operating system, an Intel(R) Core, and 8GB of RAM. Python was utilized as a programming language on the Anaconda platform. The model efficiency was evaluated using the next metric.

5.1 Outcome by the Proposed Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM Method

The Dataset contains 33,920 out of which 11,956 cases of COVID-19, 11,263 cases of non-COVID infections, such as bacterial or viral pneumonia, and 10,701 normal cases. Out of a total of 33,920 images, on the test dataset, the proposed model yielded a 98.6% accuracy rate. Figure 4,

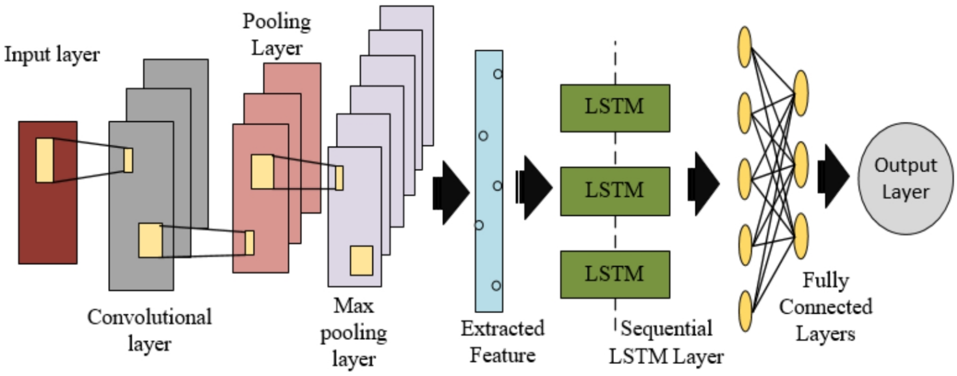

Fig. 2: CNN-LSTM Architectural Diagram.

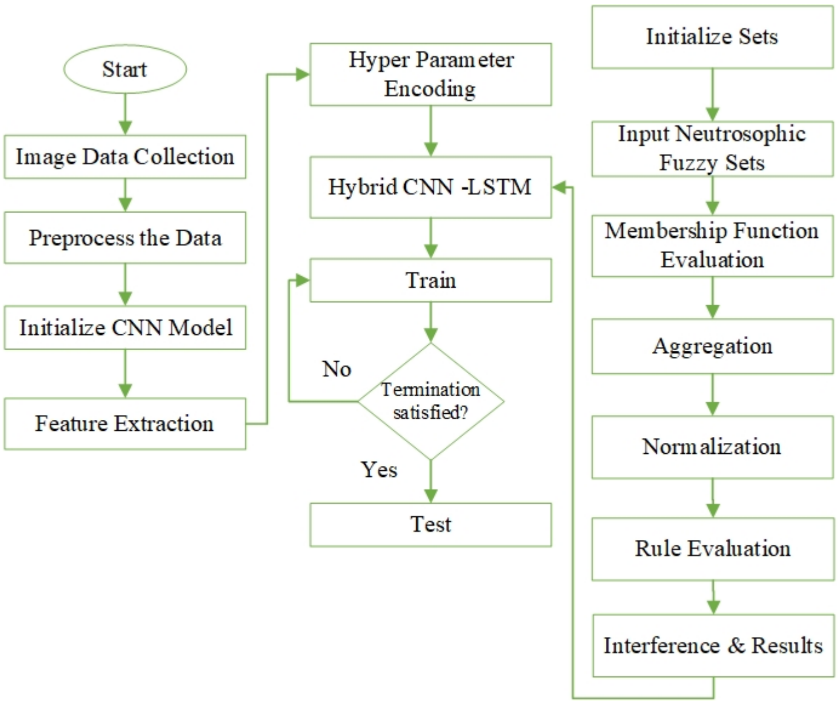

Fig. 3: Flowchart of the Proposed Neutrosophic Fuzzy Logic-Based Hybrid CNN-LSTM Method.

displays the X-Ray chest images (COVID 19, Pneumonia and normal) which are effectively classified by the suggested Neutrosophic Fussy based CNN-LSTM Model.

5.2 Performance Evaluation

The cases that the model properly identified as being under the positive category are known as True Positives. False Negatives are situations that could have been categorised as positive but were instead wrongly labelled as negative outcomes. Significant recall is preferred when correctly classifying every case of a certain class is essential because losing a positive occurrence (i.e., a false negative) has a significant cost. The model was evaluated using these parameters. They are shown below:

5.2.1 Accuracy

Accuracy is crucial to take into account other metrics like precision, recall, F1-score, and confusion matrices based on the details and characteristics of the task to be classified. Comparing the ground truth (actual) labels for

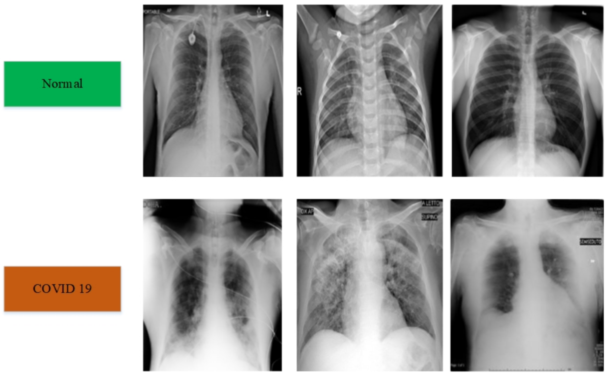

Fig. 4: Demonstration of Results by the Proposed Method.

your test dataset with the predicted class labels produced by your CNN in order to determine the accuracy. If the projected label matches the actual label for an image in the test dataset, increase the "Number of Correct Predictions." then divide this count by the "Total Number of Predictions" after processing all the test photos to determine the accuracy.
Accuracy is commonly determined by applying the following Eqn. (20)

$$Accuracy = \frac{RN + RP}{RP + AP + RN + AN} \tag{20}$$

Where, 'RN' means true negative ;'RP' means true positive ; 'AP' means false positive ; 'RN' means true negative; 'AN' means false negative.

5.2.2 Precision

Precision is a frequently measured parameter, mainly in machine learning and statistics. It evaluates how well a model predicts the future in the positive. Precision is denoted as the ratio of accurate forecasts to all reliable forecasts. It is frequently used with additional metrics for classification models, such as recall, F1-score, and accuracy.
The formula for precision in Eqn. (21) is as follows:

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \tag{21}$$

True Positives (TP) are the quantity of correctly predicted positive outcomes. False Positives (FP) are the quantity of negative events that the model mistakenly read as positive. The level of precision has a range from 0 to 1, with 1 denoting perfect precision (all correct positive predictions), and 0 denoting that no correct positive predictions were made. Dataset is needed with the model's predictions and the actual ground truth labels in order to employ this equation. Then, using the method outlined above, count the real positives and the negatives to determine precision.

5.2.3 Recall (sensitivity)

"Recall" often refers to one of the outcome indicators used to assess the model's efficacy in a task involving classification, particularly in binary or multi-class classification issues. Sensitivity and true positive rate are other names for recall. Recall in refers to the model's capacity to accurately identify each pertinent instance of a given class present in the dataset. Out of all real positive occurrences for a given class, it calculates the percentage of true positive predictions (properly detected instances of that class). Recall can be defined as mathematically in Eqn. (22)

$$Recall\,(sensitivity) = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{22}$$

5.2.4 Specificity

The proportion of accurately anticipated negative observations to all actual negative observations is defined as specificity. This Eqn. (23)is used to compute it:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \tag{23}$$

Specificity is frequently shown against sensitivity (True Positive Rate) at different categorization levels within the framework of the ROC curve. A high specificity number means that the occurrences of the negative class are accurately identified by the model, and they are not being incorrectly classified as positive.

5.2.5 F1-Score

The F1 score is a mainly used statistic to evaluate the sorting model's performance, especially those that are effective at detection and classification, in classification tasks. The F1 score is particularly useful in datasets that are unbalanced meaning that one class significantly outnumbers the other. The following Eqn. (24) is used to determine the F1 score:

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{24}$$

To take into account both in your evaluation, the F1 score offers a helpful measure of recall and precision that is neutral. To choose between precision and recall, as is frequently the case in classification jobs, it is a useful metric to use.

Table 1: The Suggested Method's Performance Metrics are Compared to those of Existing Methods.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score
COVID CAPS [35]	95.7	90	95.8	92
Bayesian CNN [36]	97	92.55	94.25	90
Deep Feature + SVM [37]	95.38	90.18	85.52	86
DCNN + BPNN [38]	89.53	84.19	92.02	89
Proposed Neutrosophic Fuzzy based CNN-LSTM	98.6	98.2	97	96

5.2.6 AUC

The whole area under the Receiver Operating Characteristic curve is represented by a single scalar number called the AUC. A model's performance across various classification thresholds is shown graphically by the ROC curve, which plots the True Positive Rate (sensitivity) versus the False Positive Rate (one-specificity).The AUC has a range of 0 to 1, where:

1.The model performs no better than chance, according to an AUC of 0.5.
2.AUC > 0.5 denotes performance that is superior than chance, and higher values signify improved discriminative capacity.

Reliability of the model to differentiate between positive and negative examples is shown by a high AUC value, which is independent of the particular classification threshold. AUC offers a succinct assessment of the model's capacity to effectively classify and distinguish between positive and negative examples across a range of threshold values.

The suggested model's accuracy is displayed in Table 1. It shows the Accuracy (98.6%), Sensitivity (98.2%), Specificity (95.8%) and F1-score (92%) of the proposed approach with traditional methods. The accuracy of the suggested method Neutrosophic Fuzzy based CNN-LSTM (98.6%) is greater than the traditional approaches like COVID CAPS (95.7%), Bayesian CNN (97%), Deep Feature + SVM (95.38%) and DCNN (89.53%).

Figure 5, shows a graphical representation of the suggested performance metrics in comparison to the current methods. The CNN-LSTM model demonstrates the highest accuracy across all five categories COVID CAPS (95.7%), Bayesian CNN (97%), Deep Feature + SVM (95.38%) and DCNN (89.53%)., with 98.6% high accuracy.

In Figure 6, the accuracy for testing and training are plotted against epochs. It is evident that the CNN-LSTM fits data more quickly because the accuracy and loss ratio overall graphs have steadied at intervals of 100. A sizable dataset of X-ray images is used to train the CNN-LSTM model. The system's hyper parameters are adjusted using

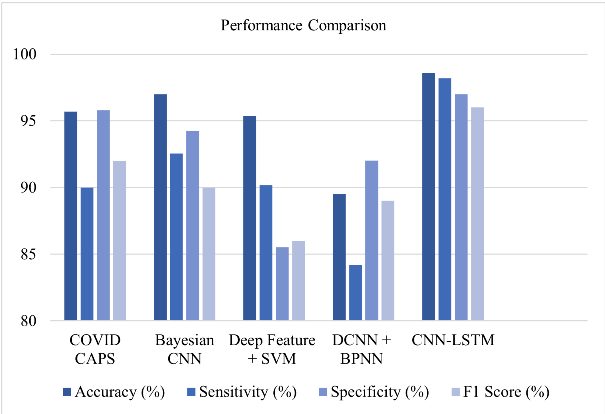

Fig. 5: Visual Representation of the Performance Measures of the Suggested Method Using Traditional Methods.

Fig. 6: The Suggested Method's Graphical Representation for both Training and Testing Accuracy.

Neutrosophic fuzzy logic, which increases the model's sensitivity and accuracy.

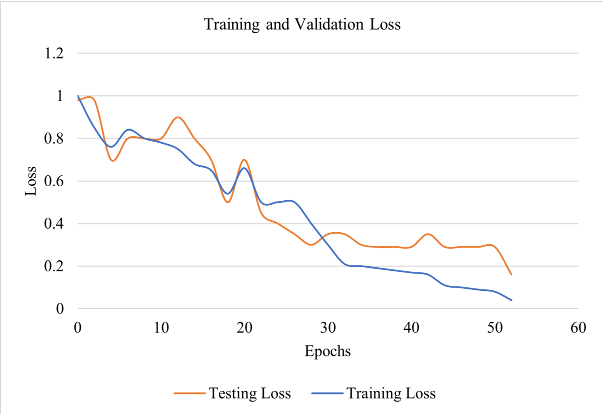

Fig. 7: The Proposed CNN-LSTM's Training and Testing Loss is Illustrated Graphically.

The loss values against epochs are shown in Figure 7. It shows the overall loss from the proposed Neutrosophic Fussy based CNN-LSTM Model.

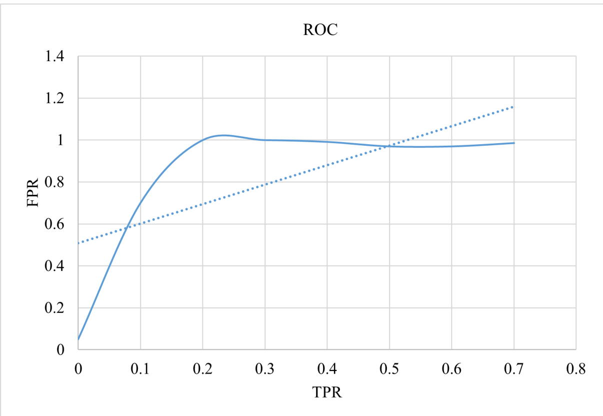

Fig. 8: TThe Proposed CNN-LSTM's ROC is Illustrated Graphically.

The FPR against TPR are shown in Figure 8. It shows the ROC graph from the proposed Neutrosophic Fussy based CNN-LSTM Model.

6 Conclusion and Future Work

In conclusion, the incorporation of Neutrosophic Fuzzy Logic into a hybrid CNN-LSTM model exhibits encouraging outcomes for precise chest X-ray categorization in COVID-19 prediction. Using Neutrosophic Fuzzy Logic, this method combines the flexibility and capacity to handle uncertainty with the advantages of both convolutional neural networks (CNN) and long short-term memory (LSTM) networks. The model's ability to reliably identify COVID-19 instances from chest X-ray pictures highlights the possibility of early and accurate diagnosis assistance, which would greatly improve effective disease management and treatment. The Proposed model's ability to successfully identify COVID-19 infection from chest X-ray images highlights its potential as a helpful tool for radiologists and physicians. Prompt isolation and treatment of COVID-19 are essential for preventing the disease's spread and enhancing patient outcomes. This requires early and precise diagnosis of the virus. Furthermore, this approach has the potential to alleviate the strain on healthcare systems by supporting the process of resource allocation and triaging, particularly in light of the current epidemic. More research could concentrate on growing the dataset, improving the architecture of the model, and investigating the integration of other cutting-edge technologies or methodologies, with the ultimate goal of real-time applications in clinical settings. If these developments continue, they might completely transform the medical diagnostics industry and greatly enhance the treatment of infectious disorders such as COVID-19. Furthermore, investigating transfer learning techniques and including multimodal data sources may enhance the model's functionality and suitability for use in various healthcare environments.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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