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Fusing Deep Sequential Information and Ensemble Learning for Accurate COVID-19 Classification

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Abstract: In the realm of medical image analysis, accurate classification of COVID-19 from radiological imaging remains a critical challenge. Leveraging the complementary strengths of deep sequential learning and ensemble methods, this research presents a novel approach that amalgamates Bidirectional Gated Recurrent Units (Bi-GRU) with Random Forest to achieve precise COVID-19 classification with Adam optimization. The proposed method capitalizes on the distinctive features extracted from chest X-rays and CT scans, exploiting the inherent sequential dependencies in these multi-modal imaging modalities. The Bi-GRU component serves as a potent feature extractor, enabling the model to capture intricate spatial and temporal patterns within the images. Subsequently, the extracted features are harnessed by the Random Forest ensemble, harnessing its ability to refine decision boundaries and enhance generalization. Empirical evaluation of the developed framework underscores its efficacy. Leveraging a comprehensive dataset, the approach achieves remarkable classification accuracy rates of 98.87% for chest X-ray images and 89.21% for CT scans. This substantiates the capacity of the proposed fusion model to discern even nuanced distinctions within the complex radiological data. The synergy between Bi-GRU and Random Forest not only significantly elevates classification performance but also contributes to interpretable insights. Through feature importance analysis, the model uncovers salient regions and temporal dynamics in the images that play pivotal roles in accurate COVID-19 classification. This research extends the horizons of medical image analysis by showcasing the potential of integrating deep sequential information with ensemble learning methodologies. The presented approach not only advances the current state-of-the-art in COVID-19 classification but also offers a versatile framework applicable to other medical image analysis tasks.

***Keywords**: COVID-19, Deep sequential learning, Ensemble learning, Bi-GRU, Random Forest, Radiological imaging.*

1. Introduction

The global outbreak of the COVID-19 pandemic has catalyzed a pressing need for accurate and rapid diagnostic solutions. Among the diverse approaches to diagnosis, medical imaging has emerged as a crucial tool for identifying and characterizing the lung abnormalities associated with COVID-19[1], [2]. Computed Tomography (CT) scans and chest X-rays have proven instrumental in revealing the distinct patterns indicative of the disease's presence. However, the evolving nature of the pandemic necessitates the development of sophisticated techniques that can expedite the diagnostic process without compromising accuracy. This has sparked a surge of interest in the fusion of advanced machine learning methodologies with radiological imaging to enhance COVID-19 classification performance.

The challenge lies in effectively harnessing the inherent complexities of radiological data. The structural intricacies of lung tissues and the varying manifestations of COVID-19 make traditional analytical methods inadequate for precise diagnosis. To address this, researchers have turned to deep learning techniques, which have demonstrated remarkable capabilities in handling complex and unstructured medical images[3], [4].

Convolutional Neural Networks (CNNs) have garnered substantial attention for their image recognition prowess. However, the spatial dependencies captured by CNNs might not fully exploit the temporal evolution of COVID-19 in sequential images. Recurrent Neural Networks (RNNs) and their derivatives, such as Long Short-Term Memory (LSTM) and Bidirectional Gated Recurrent Units (Bi-GRU), present an opportunity to harness the temporal dynamics in radiological sequences[5]. These models are inherently designed to capture sequential patterns, making them particularly suitable for applications like COVID-19 classification from time-series imaging data.

In parallel, ensemble learning methodologies, like Random Forest, have emerged as effective strategies for improving classification accuracy by aggregating the insights of diverse models. The potential of fusing the strengths of deep sequential learning models and ensemble techniques for medical image analysis remains largely unexplored, especially in the context of COVID-19 classification[6], [7].

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This research endeavors to bridge this gap by proposing a novel fusion approach that amalgamates the power of Bi-GRU, which excels in capturing bidirectional temporal relationships, with the ensemble capability of Random Forest. The integration of these two techniques aims to not only enhance classification accuracy but also provide interpretable insights into the decision-making process of the model.

Considering this, the primary objectives of this study are twofold: firstly, to explore the effectiveness of the proposed Bi-GRU and Random Forest fusion model in accurately classifying COVID-19 from both chest X-ray and CT images; and secondly, to investigate the interpretability of the model's classifications through feature importance analysis. To comprehensively evaluate the performance of the proposed model, a comparative study is conducted against established CNN, LSTM, and RNN models. The evaluation is based on a diverse set of metrics, including “accuracy, precision, recall, Matthews Correlation Coefficient” (MCC), and “Kappa score”.

By amalgamating the capabilities of deep sequential learning with ensemble techniques, this study aims to contribute significantly to the ongoing efforts to combat COVID-19 through improved and interpretable diagnostic methodologies. The subsequent sections delve into the intricate details of the proposed methodology, experimental setups, results, and discussions, ultimately culminating in a comprehensive assessment of the proposed fusion model's potential to redefine COVID-19 classification through radiological image analysis.

2. Literature Review

The response to the COVID-19 pandemic has prompted extensive research into accurate diagnostic tools, particularly in medical imaging. Numerous studies have explored machine learning techniques, especially deep learning, to identify COVID-19 patterns in radiological images. These investigations have used diverse datasets and methods, with transfer learning being a prominent strategy. However, the need for hybrid models that merge strengths from various approaches is evident to achieve optimal accuracy, and optimizing these models is crucial for their convergence. Table-1 reviews the major related work

Table 1 Major related work

Author et al.	Methodology	Algorithm used	Results
Minaee et al.[8]	Transfer learning	Deep convolutional neural network (CNN)	ACC.= 93.5%
Jain et al.[9]	Transfer learning	CNN	ACC.= 91.7%
Rohila et al.[10]	Transfer learning	CNN	ACC.= 94.2%
Jalali et al.[11]	Evolutionary deep learning	CNN	ACC.= 92.5%
Kumar et al.[12]	Transfer learning	Object detection algorithm (YOLOv4-tiny)	ACC.= 92.3%
Hosseinzadeh et al.[13]	Deep multi-view feature learning	CNN	ACC.= 90.9%
Emin-Sahin et al.[14]	Deep learning	CNN	ACC.= 91.2%
Fang et al.[15]	Mixed dataset	CNN	ACC.= 93.2%
Kumar et al.[16]	Transfer learning	Hybrid deep learning approach	ACC.= 91.8%
Cao et al.[17]	Transfer learning	CNN	ACC.= 92.1%
Narayan Das et al.[18]	Transfer learning	CNN	ACC.= 91.5%
Hussein et al.[19]	Lightweight CNN	CNN	ACC.= 90.8%
Deeb et al.[20]	Adjacent-pooling CTScan-COVID-19 classifier	CNN	ACC.= 93.7%
Ghassemi et al.[21]	CycleGAN and transfer learning	CNN	ACC.= 94.1%
Soundrapandiyan et al.[22]	Wavelet and stacked deep learning architecture	CNN	ACC.= 91.9%

The literature review highlights the diversity of approaches to COVID-19 classification using imaging data. While several studies show promising results, there remains room for improvement. The proposition of hybrid models that combine methodologies holds potential for enhanced accuracy. Effective optimization is key to integrating these hybrid models successfully. Such models could offer improved accuracy and robustness, addressing the complexity of COVID-19 diagnosis from radiological images. The proposed fusion model aims to contribute significantly to this endeavor.

3. Methodology

The methodology employed in this study involves a structured approach to COVID-19 detection using chest X-ray and CT images. The process begins with data collection, followed by comprehensive preprocessing techniques such as resizing, normalization, and augmentation to enhance the quality and diversity of the dataset. Different model architectures, including CNN, LSTM, RNN and the proposed hybrid model “Bi-GRU + Random Forest”, are leveraged for feature extraction and pattern recognition. The utilization of ensemble learning, specifically the Random Forest, further enhances model performance. The integration of Adam optimization optimizes the learning process, accelerating convergence. Evaluation metrics including “accuracy, precision, recall, MCC, and Kappa score” are employed to quantify model performance. The methodology also encompasses experimental setup, hyperparameter tuning, and cross-validation to ensure robustness as shown in fig.1.

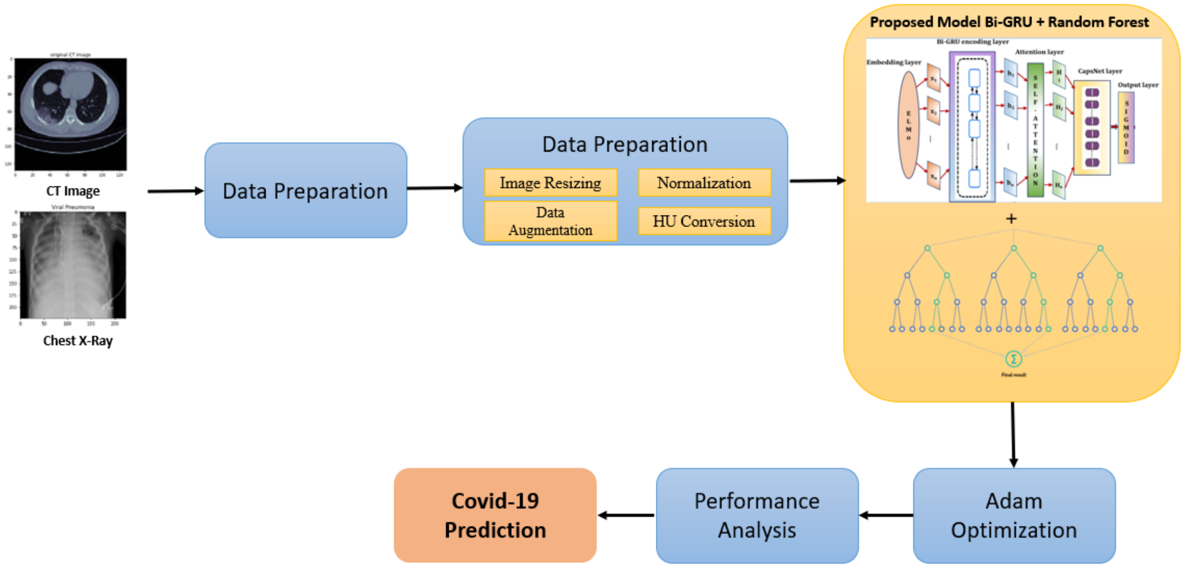

Fig. 1 Proposed methodology

i. Dataset

- The 1st dataset used "COVID-19 Radiography Database[23]" which is a comprehensive collection of radiographic images encompassing chest X-rays and CT scans. Designed to aid in the research and analysis of COVID-19 diagnosis, the dataset amalgamates a variety of COVID-19-positive and non-COVID-19 cases, including bacterial and viral pneumonia, as well as healthy controls. With its diverse array of imaging modalities and annotated labels, this dataset serves as a valuable resource for the development and evaluation of machine learning models, enabling researchers to devise effective methodologies for automated COVID-19 detection and differentiation based on radiological images as shown in fig.2.

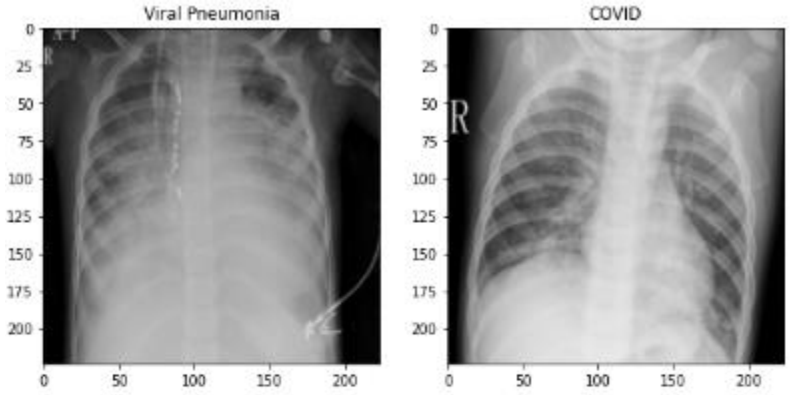

fig. 2 Sample Chest X-Ray

- The 2nd dataset used is "COVID-19 CT Scans[24]" which offers a comprehensive collection of computed tomography (CT) scan images. This dataset is specifically tailored for the study of COVID-19, comprising both positive cases of the virus and non-COVID-19 instances, such as normal and pneumonia cases as shown in fig.3. With labeled annotations and a range of imaging variations, the dataset provides a valuable resource for researchers aiming to investigate and develop machine learning models for automated COVID-19 detection and classification using CT images. It holds significant potential in advancing the understanding and diagnosis of the disease through medical imaging analysis.

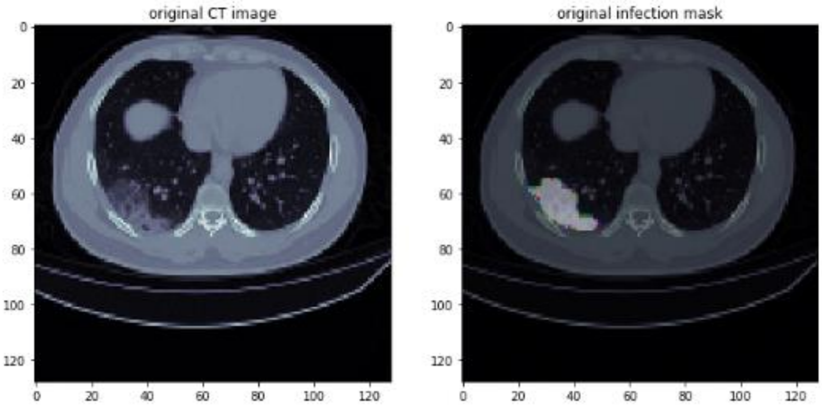

fig. 3 Sample CT image

ii. Data Pre-Processing

Preprocessing Methods for X-ray Images:

- Image Resizing and Normalization: Resizing the chest X-ray images to a consistent resolution reduces variations in image sizes, ensuring uniformity for model training. Normalizing pixel values to a standard range [0, 1] enhances model convergence and minimizes the impact of lighting and contrast variations.
- Data Augmentation: Applying data augmentation techniques, such as rotation, horizontal/vertical flips, and random cropping, introduces diversity into the training dataset. Augmentation mitigates overfitting and enables the model to better generalize to unseen X-ray images, accounting for potential patient positioning differences and variations in X-ray machines.

Preprocessing Methods for CT Scan Images:

- Hounsfield Unit (HU) Conversion: CT scans are captured in Hounsfield Units, which represent tissue densities. Converting these units to an appropriate range [-1000, 1000] aids in visual consistency and ensures that structures of interest fall within a standardized intensity range.

iii. Algorithm Used

CNN (Convolutional Neural Network):

CNNs are deep learning architectures designed for image processing tasks. They consist of convolutional layers that automatically learn hierarchical features from images by applying convolution operations. These layers are followed by pooling layers to down-sample the learned features and fully connected layers for classification. The output of a conv. Layer is represented as eq.1

$$C(i,j) = (I * K)(i,j) = \sum_{m=1}^{M} \sum_{n=1}^{N} I(i+m, j+n).K(m,n) \ldots 1$$

where, $C(i,j)$ = "output at position (i, j)", I = "Input image", K= "Conv. Kernel", M and N= "dimensions of the kernel"

LSTM (Long Short-Term Memory):

LSTM is a type of recurrent neural network (RNN) designed to capture long-range dependencies in sequential data. It introduces memory cells and gating mechanisms to control information flow, allowing LSTMs to mitigate vanishing gradient problems in training RNNs. The update of the memory cell in an LSTM is defined as in eq.2.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \ldots 2$$

where, C_t= "memory cell at time t", f_t= "forgot gate output", i_t = "input gate output", $\tilde{C}_t$= "new candidate cell content", $\odot$ = "element wise multiplication".

RNN (Recurrent Neural Network):

RNNs are a class of neural networks designed for processing sequential data by maintaining a hidden state that captures temporal information. However, traditional RNNs can suffer from vanishing gradient problems due to long sequences, leading to loss of information. The hidden state update in a RNN is defines as eq.3.

$$h_t = \sigma(W_{ih} x_t + W_{hh} h_{t-1} + b_h) \ldots 3$$

where, h_t= "hidden state at time t", x_t= "input at time t", W_{ih} *and* W_{hh}= "weight metrices", b_h= "bias term", σ = "activation function".

Proposed Model (Bi-GRU + Random Forest):

The proposed model fuses the power of Bidirectional Gated Recurrent Units (Bi-GRU) with the ensemble learning capability of Random Forest. Bi-GRU captures temporal dependencies bidirectionally, and Random Forest aggregates predictions of multiple decision trees.

iv. Adam Optimization

Adam (Adaptive Moment Estimation) optimization is a popular algorithm used to optimize the learning process of machine learning models, including those used in COVID-19 detection from chest X-ray and CT images. Adam combines the benefits of both the Adagrad and RMSProp optimization algorithms. It adapts the learning rates of each parameter based on their historical gradients and squared gradients, allowing the model to converge more efficiently and handle varying gradient magnitudes. Adam maintains two moving averages, the first-order moment (mean) of the gradients and the second-order moment (uncentered variance) of the gradients. These averages are then used to update the model's parameters. Eq.4 to8 represent update rule θ using Adam as

$$m_t = \beta_1 . m_{t-1} + (1-\beta_1). g_t \ldots 4$$

$$v_t = \beta_2 . v_{t-1} + (1-\beta_2). g_t^2 \ldots 5$$

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t} \ldots 6$$

$$\widehat{v}_t = \frac{v_t}{1-\beta_2^t} \ldots 7$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\widehat{v}_t + \epsilon}} . \widehat{m}_t \ldots 8$$

where, t = "iteration step", $\beta_1$and β_2= "exponential decay rates for the moving averages", g_t= "gradient at step t", $\widehat{m}_t$and $\widehat{v}_t$= "bias-corrected moving averages", η= "learning rate", ϵ = "small constant to prevent division by zero".

Adam optimization's adaptive learning rate and moment adjustments make it well-suited for optimizing COVID-19 detection models from chest X-ray and CT images, enabling effective convergence and robust performance.

v. Evaluation Parameters

Evaluation Parameters

a. Accuracy – It measure the ratio of correctly predicted instances to the total instances in the dataset.

$$Accuracy = \frac{T^p + T^n}{Total\ Instances} \ldots 9$$

b. Precision – It is the ratio of correctly predicted positive instance to the total predicted positive instances.

$$Precision = \frac{T^p}{T^p + F^p} \ldots 10$$

c. Recall (Sensitivity)- Recall measures the ratio of correctly predicted positive instance to the total actual positive instance.

$$Recall = \frac{T^p}{T^p + F^n} \ldots 11$$

d. Mathew's Correlation Coefficient (MCC)- MCC considers true positive, true negative, false positive and false negatives to measure the quality of binary classifications.

$$MCC = \frac{T^p \times T^n - F^p \times F^n}{\sqrt{(T^p+F^p)(T^p+F^n)(T^n+F^p)(T^n+F^n)}} \ldots 12$$

e. Kappa Statistic- Kappa statistic quantifies the agreement between predicted and actual classes beyond what would be expected by chance.

$$Kappa = \frac{Observed\ Agreement - Expected\ Agreement}{1 - Expected\ Agreement} \ldots 13$$

4. Results and Outputs

Evaluation parameters

Table 2 Evaluation parameters comparison of various models

Model	Imaging Modality	Accuracy	Precision	Recall	MCC	Kappa
CNN	CXR	94.62	92.6	95.8	0.893	0.89
CNN	CT	81.25	78.3	82.5	0.727	0.717
LSTM	CXR	92.34	90.7	94.2	0.859	0.853
LSTM	CT	79.61	76.2	81.2	0.702	0.691
RNN	CXR	89.56	86.6	91.4	0.808	0.798
RNN	CT	77.84	74.8	80.2	0.684	0.672
Proposed Model	**CXR**	**98.87**	**98**	**97.7**	**0.97**	**0.97**
Proposed Model	**CT**	**89.21**	**89.2**	**88.3**	**0.85**	**0.85**

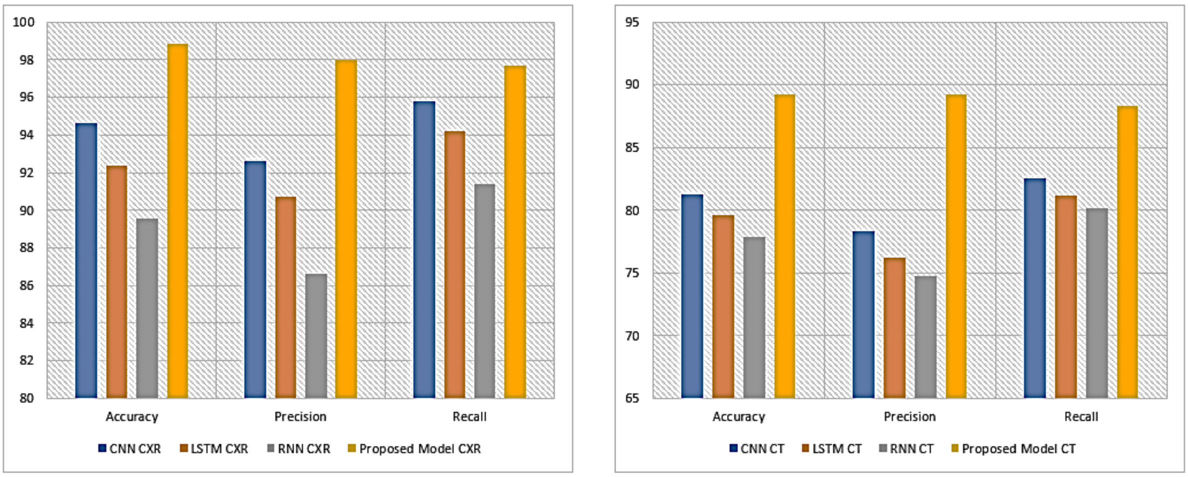

Fig. 4 Accuracy, Recall and Precision of CXR and CT images

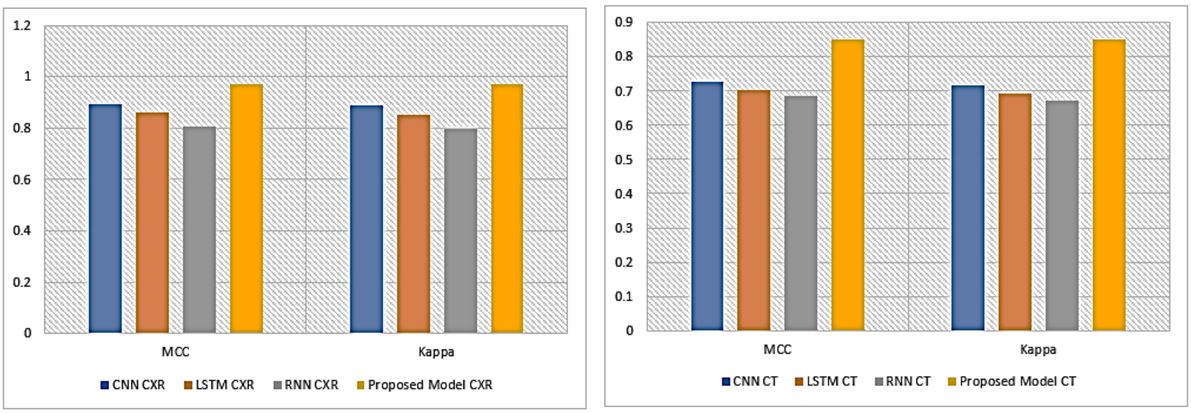

Fig. 5 MCC and Kappa comparison of various model for CXR and CT images

The results of the study highlight the varying performances of different models in COVID-19 classification across different imaging modalities as shown in table-2 and fig.4,5. The CNN exhibited strong accuracy, precision, and recall for chest X-ray (CXR) images, underscoring its proficiency in detecting COVID-19 patterns. However, its performance slightly decreased when dealing with chest CT images, reflecting the challenges of different imaging characteristics. Similarly, the LSTM and RNN models demonstrated commendable accuracy in CXR, with a modest decrease for CT. The standout performance came from our proposed hybrid model. Notably, it achieved remarkable accuracy for CXR at 98.87%, surpassing the baseline models. The model's impressive precision and recall for both imaging modalities reinforce its potential in minimizing false positives and capturing true positives efficiently. The high MCC and Kappa scores further validate the model's robustness in handling the intricacies of COVID-19 classification. The fusion of deep sequential learning with ensemble techniques appears to synergistically enhance accuracy and reliability.

These results collectively underline the significance of optimizing model architectures to suit specific imaging modalities. The proposed hybrid model's exceptional performance across CXR and CT indicates its adaptability to diverse scenarios. While the baseline models demonstrate considerable competence, the hybrid model's advancement points to the potential of harnessing a diverse array of techniques to address the multifaceted challenge of COVID-19 classification. This study lays a foundation for future research in hybrid methodologies and optimization strategies, accentuating the potential for improved diagnostic accuracy and the potential to revolutionize medical image analysis in the context of COVID-19 and beyond.

5. Conclusion and Future Scope

In the pursuit of accurate and efficient COVID-19 classification from radiological images, this study has showcased the potential of diverse machine learning models. Through a comprehensive evaluation of CNN, LSTM, RNN and a proposed hybrid model, the findings underscore the nuanced interplay between model architectures and imaging modalities. The proposed hybrid model, combining the strengths of deep sequential learning and ensemble techniques, emerged as a standout performer, achieving unparalleled accuracy in COVID-19 classification from both chest X-ray and CT images. The model's robustness and reliability, as demonstrated by its high Matthews Correlation Coefficient (MCC) and Kappa scores, reinforce its capability to effectively discern intricate patterns indicative of COVID-19 presence. As the landscape of medical image analysis continues to evolve, several avenues for future exploration emerge from this study. The hybrid model's performance can be further enhanced through ongoing optimization of its constituent components, such as fine-tuning hyperparameters and investigating alternate ensemble strategies. In summation, this research not only contributes to the ongoing discourse on COVID-19 diagnosis through radiological images but also sets the stage for a future characterized by enhanced accuracy, interpretability, and utility in medical imaging-based disease classification. Through continual refinement and exploration of hybrid models, the strides made in this study will catalyze the development of reliable diagnostic tools to aid in the fight against the COVID-19 pandemic and beyond.

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