Viral Pneumonia Detection Using Deep Learning

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Presentation Outline:

- Introduction
- Literature Review
- Implementation Algorithms
- Results
- Comparison
- Conclusion

Introduction

Pneumonia is a major global health issue, causing significant illness and death. Diagnosing it remains challenging despite advances in imaging.

This presentation will cover:

- Breakdown of the algorithms used for detecting viral pneumonia.
- Overview of the model's performance on test data, highlighting key metrics.
- Comparison of CNN and LSTM based in different activation functions.

Problem Statement

Develop an automated system using deep learning to accurately detect pneumonia from chest X-ray images. This system should:

- **Improve Accuracy**: Achieve diagnostic precision comparable to expert radiologists, reducing false positives and negatives.
- **Increase Efficiency**: Speed up the diagnostic process for quicker treatment decisions.
- **Ensure Scalability**: Be adaptable for use in various healthcare settings, including those with limited resources.
- **Enhance Generalization**: Perform reliably across different populations and imaging conditions.

Literature Review

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Title	Year	Authors	Methodology	Results	Remarks
Modelling of Neutrosophic Set-Based k-Nearest Neighbors Classifier for Virus Pneumonia and COVID-19 Recognition	2024	Imène Issaoui, Afef Selmi	The authors propose a novel approach called Deep Learning with Neutrosophic Set-Based k-Nearest Neighbors Classifier for Disease Detection (DLNSKNN-DD). This method combines deep learning techniques with neutrosophic set theory for improved classification. The key components of the methodology include Feature extraction using ResNet50v2, Parameter tuning of ResNet50v2 using Adadelta optimizer, Classification using a Neutrosophic Set-Based k-Nearest Neighbors (NSKNN) model, The NSKNN classifier incorporates neutrosophic memberships (truth, indeterminacy, and falsity) to enhance the traditional k-NN algorithm's performance. The study utilizes a chest X-ray dataset containing 305 samples across 6 classes.The DLNSKNN-DD method achieved 98.44% average accuracy acrosss multiple metrics.	The DLNSKNN-DD method achieved high accuracy across multiple metrics:With 70% training data: 98.44% average accuracy, 95.19% precision, 84.26% sensitivity, 97.87% specificity, and 89.01% F-score.With 30% testing data: 99.64% average accuracy, 99.76% precision, 95.83% sensitivity, 99.28% specificity, and 97.50% F-score.These results outperformed several other models including SCODL-DDC, InceptionV3, ResNet50, VGG16, and others across various metrics.	The authors propose a novel approach combining deep learning and neutrosophic set theory for improved lung disease classification, particularly for COVID-19 and pneumonia. Their DLNSKNN-DD method outperforms other models in accuracy and handling uncertainty, though a small dataset limits robust validation. They suggest further research with larger datasets and a focus on model interpretability for medical applications.
A deep learning approach for classification of COVID and pneumonia using DenseNet-201	2023	Harshal A. Sanghvi, Riki H. Patel, Ankur Agarwal, Shailesh Gupta, Vivek Sawhney, Abhijit S. Pandya	The authors employed a deep learning approach using DenseNet-201 for detecting COVID-19 and pneumonia from chest X-ray images. They utilized transfer learning, freezing the pre-trained DenseNet-201 weights from ImageNet and adding custom layers for classification. The model was trained for 100 epochs using categorical cross-entropy loss and Adam optimizer. Data augmentation and a composite learning factor strategy were implemented to improve performance. The authors also developed a graphical user interface tool to assist radiologists in using the model. The study used a dataset from Kaggle containing 15,153 chest X-ray images. The proposed model achieved an overall accuracy of 99.1%, The confusion matrix showed high accuracy in classifying all three categories, with only a small number of misclassifications.	The proposed model achieved impressive results:Overall accuracy: 99.1%, Detection sensitivity: 98.5%, Specificity: 98.95%, Cohen's Kappa coefficient: 98.1%, The confusion matrix showed high accuracy in classifying all three categories, with only a small number of misclassifications.	The proposed DenseNet-201 model achieved 99.1% accuracy, outperforming other CNN architectures like ResNet50 and VGG16. The authors' comprehensive approach includes preprocessing, thorough evaluation metrics, and a graphical user interface for clinical use. While the model shows high performance, further external validation on diverse datasets and discussion of limitations would enhance the study's conclusions. Overall, the paper presents a promising approach for automated COVID-19 and pneumonia detection from chest X-rays.
Efficient Pneumonia Detection in Chest X-ray Images: Leveraging Lightweight Transfer Learning for Improved Accuracy and Practicality	2023	Bibi Qurat Ul Ain, Chen Bingcai	The researchers employed a transfer learning approach using three pre-trained lightweight models: SSD MobileNetV2, SSD MobileNetV2 FPNLite 320x320, and SSD MobileNetV2 FPNLite 640x640. They experimented with different dataset distributions, image pre-processing techniques, classification loss functions, and hyper-parameter tuning. The models were evaluated using metrics such as mean Average Precision (mAP), accuracy, recall, precision, and F1-score. The study utilized a public dataset of chest X-ray images from pediatric patients aged one to five years, treated at the Guangzhou Women and Children's Medical Center. The dataset initially contained 1,583 normal cases and 4,273 pneumonia cases. After augmentation and balancing, the final dataset comprised 8,613 training images and 1,404 testing images. The models achieved mean Average Precision (mAP) scores of 76%, 85%, and 80% respectively. Their accuracies were 81.3%, 94.6%, and 92.6% respectively. The SSD MobileNetV2 FPNLite 320x320 model demonstrated the highest performance among the three.	The models achieved mean Average Precision (mAP) scores of 76%, 85%, and 80% respectively. Their accuracies were 81.3%, 94.6%, and 92.6% respectively. The SSD MobileNetV2 FPNLite 320x320 model demonstrated the highest performance among the three.	The researchers concluded that lightweight models, particularly SSD MobileNetV2 FPNLite, achieved competitive results in pneumonia detection with 94.6% accuracy and 85% mAP. Their approach highlights the potential of efficient models for medical image analysis, especially in resource-limited settings. While promising, further validation on diverse datasets and different age groups is needed to confirm the model's robustness and generalizability in clinical scenarios.
Validation of a deep learning model for classification of pediatric pneumonia in Hong Kong	2024	Dong Wang, Boshu, Elaine Yuen Phin Lee, Andy Cheuk Nam Hwang, Kate Ching-Ching Chan, Jessica Weaver, Meghan White, Yiyun Chen, Kim S.J. Lao, Tsz K. Khan, Craig S. Roberts	The researchers employed a deep learning model with transfer learning to classify chest X-ray (CXR) images for primary endpoint pneumonia (PEP) based on World Health Organization (WHO) criteria. They compared the model's performance against a gold standard classification by a panel of radiologists. The model was applied to a dataset of pediatric CXR images, both with and without an autosegmentation algorithm to crop the images. The study used a dataset of 550 CXR images from children under 5 years of age who were hospitalized with lower respiratory tract infections or discharged with a diagnosis of all-cause pneumonia.	Without autosegmentation, the model achieved an overall accuracy of 0.815 (95% CI: 0.782-0.847), sensitivity of 0.812 (95% CI: 0.761-0.864), specificity of 0.816 (95% CI: 0.775-0.858), and an area under the receiver operating characteristic curve (AUROC) of 0.893 (95% CI: 0.867-0.919). With autosegmentation, the model's performance improved across all metrics. The overall accuracy increased to 0.875 (95% CI: 0.846-0.900), and the AUROC improved to 0.944 (95% CI: 0.926-0.961).	The researchers demonstrated that their deep learning model, previously trained on publicly available CXR datasets, could effectively identify WHO-defined PEP in an independent dataset with high accuracy compared to a consensus of trained radiologists. The implementation of autosegmentation significantly improved the model's performance, particularly for images from children under 1 year of age. The study highlights the potential for using deep learning models to increase efficiency in large-scale epidemiological studies that rely on classification of image data. However, the authors note that the model is intended for research purposes only and not for clinical diagnosis. They also acknowledge limitations such as the model's dependence on data quality and the potential need for re-validation when applied to additional external datasets.

Implementation Algorithm

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1. ## Data Preparation

   Collect Data: Gather a dataset of chest X-ray images labeled with the presence or absence of viral pneumonia.

2. ## Model Architecture Design

   Define and structure the neural network by adding layers (convolutional, pooling, and dense) that extract features from input images and make classification based on learned patterns.

3. ## Compile the Model

   Specify the loss function (categorical or binary cross-entropy).

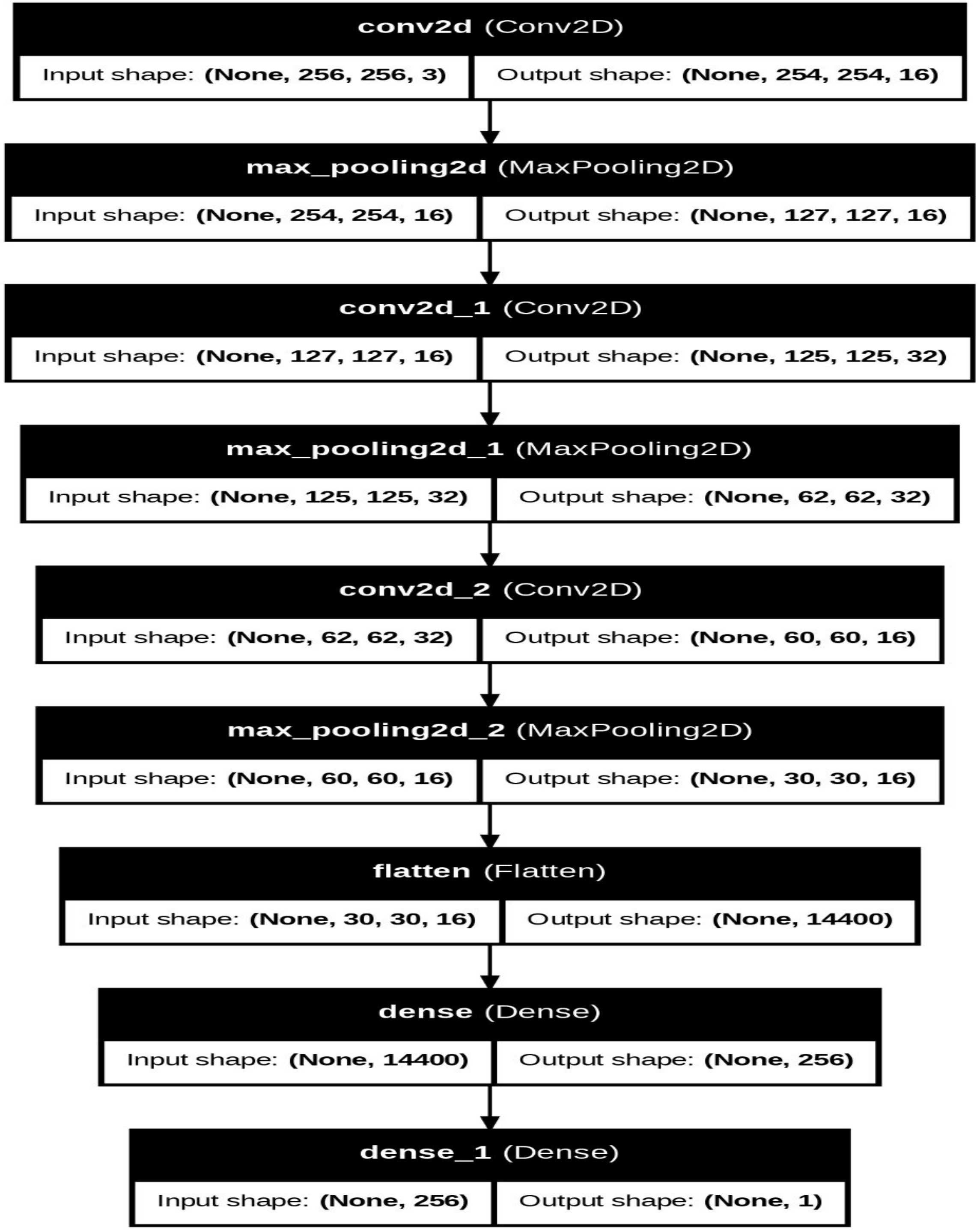
   Choose an optimizer (e.g., Adam).

4. ## Train the Model

   Fit the Model: Train the model using the training dataset.

5. ## Evaluate the Model

   Calculate performance metrics (accuracy, precision, recall, F1-score) to determine how well the model is doing.



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Convolutional Layer (Conv2D):

- Applies 16 filters (kernels) of size 3x3 to the input image.
- Each filter scans through the image and detects features such as edges, textures, and shapes.

Max Pooling Layer:

- Reduces the spatial dimensions (width and height) of the feature map from the previous layer.
- Retains only the most significant features by taking the maximum value in each pooling window (commonly 2x2).

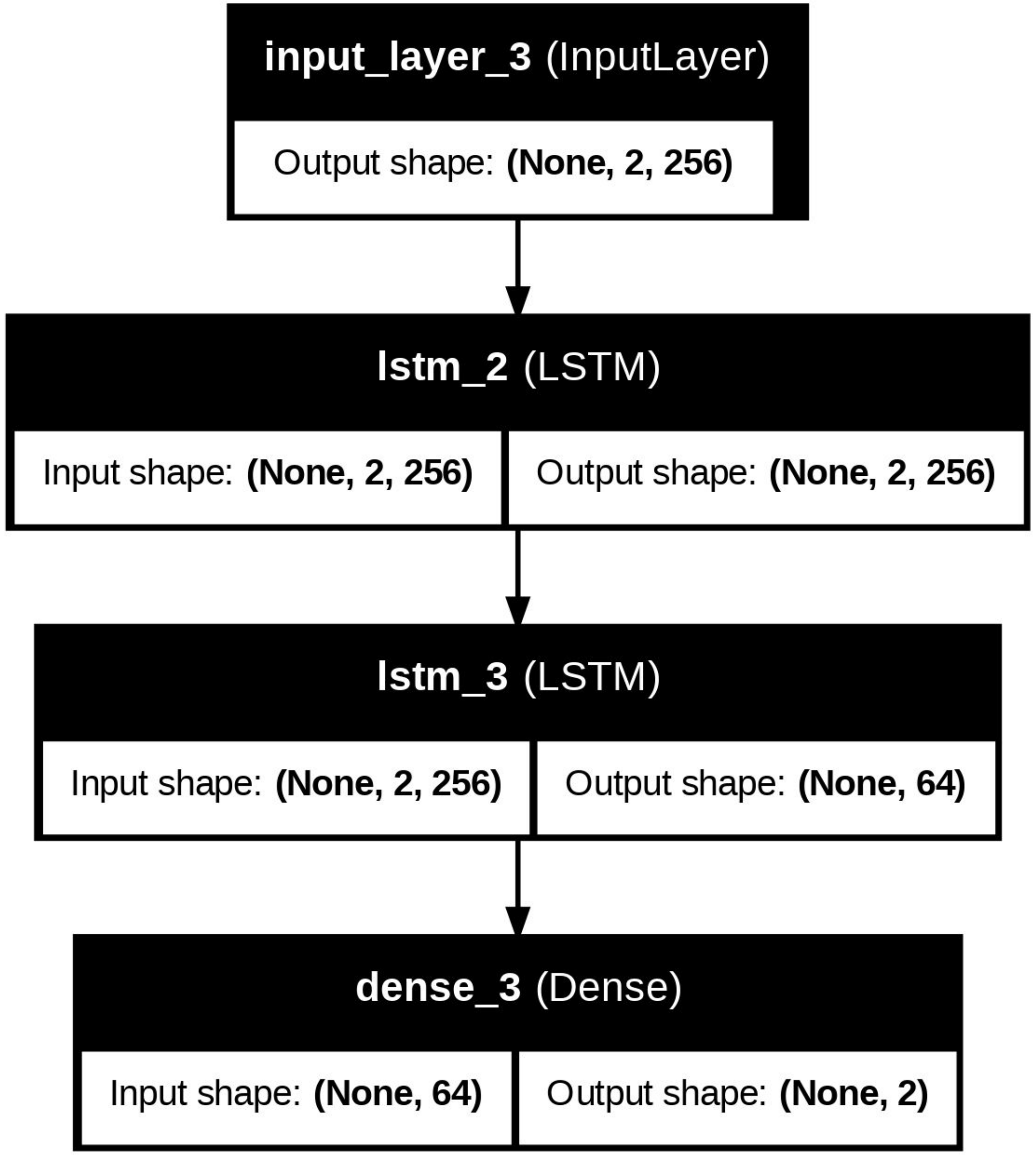
Flatten Layer:

- Converts the 3D feature maps into a 1D vector.
- This outputs a flat vector containing all features learned by the convolutional layers.

Dense Layer:

- The activation function (ReLU) introduces non-linearity.
- Uses a sigmoid activation function to provide a binary classification (pneumonia or normal).

LSTM:



Input Layer:

- This is the input layer of the model. It expects sequences with two time steps (2) and each step having 256 features.

LSTM Layer 1 :

- This LSTM layer processes the input sequence of length 2 with 256 features per step. It has 256 units and returns the output for every time step.

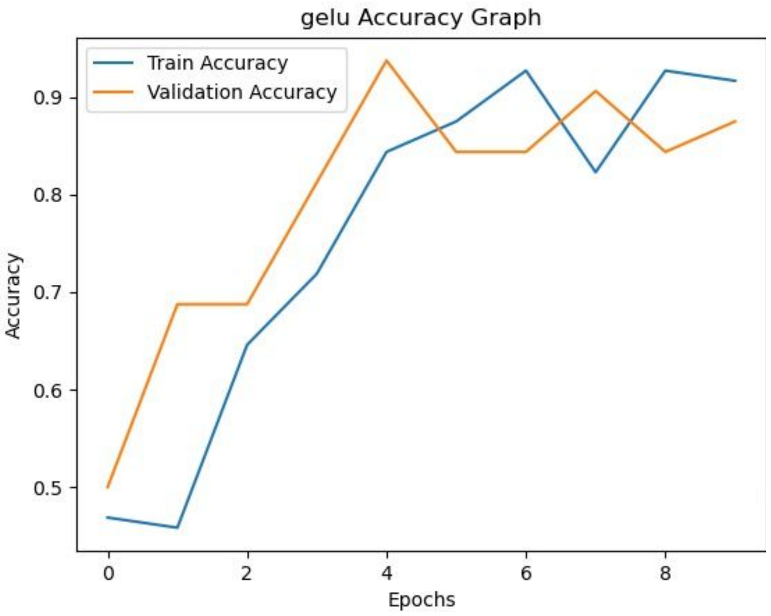
LSTM Layer 2 :

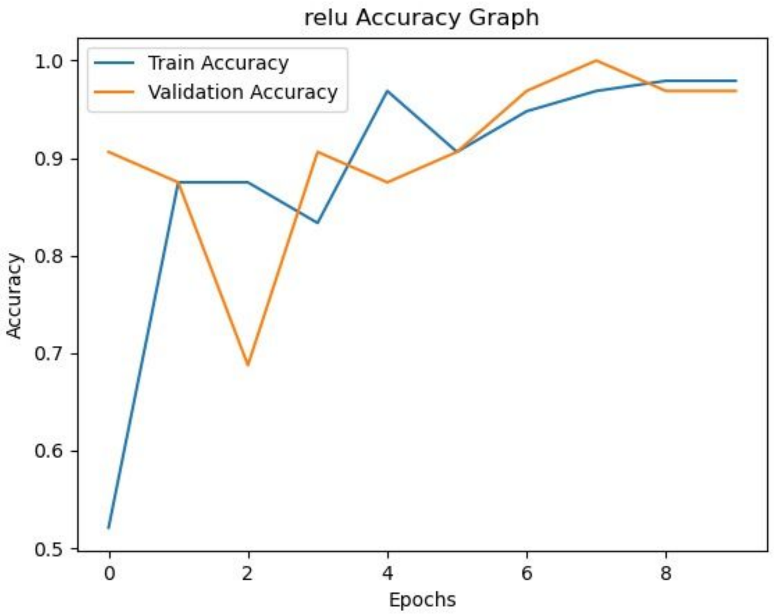
- The second LSTM layer takes the output from the first LSTM layer. It has 64 units and returns the output for the final time step only..

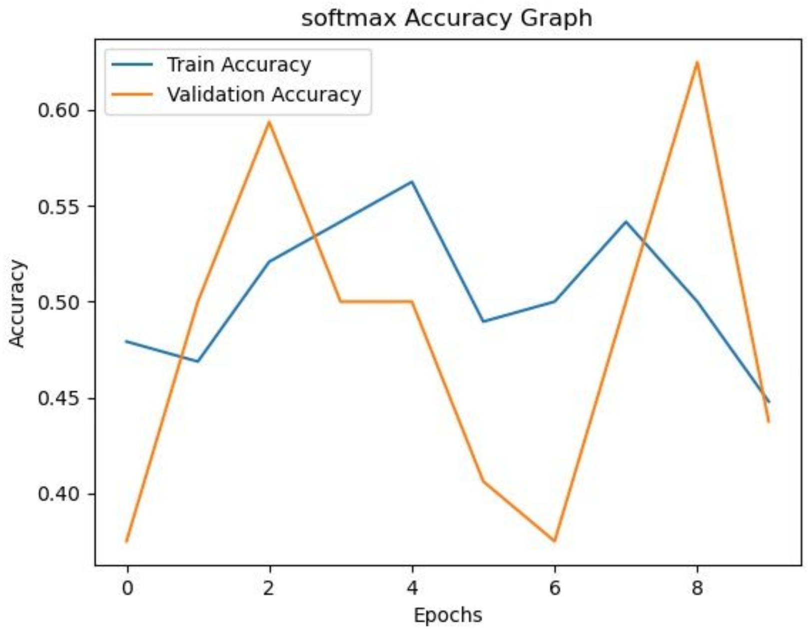
Dense Layer ::

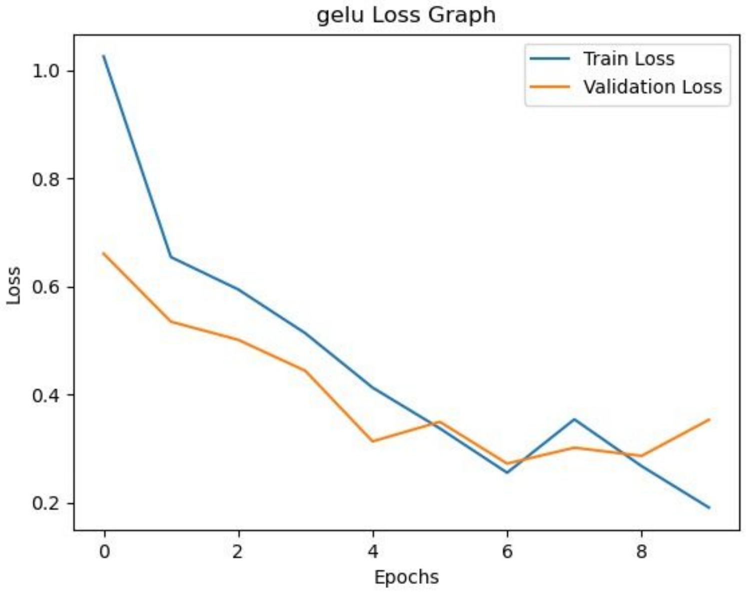
- This fully connected (dense) layer takes the 64-dimensional output from the second LSTM and reduces it to 2 dimensions. Typically, this layer is used for classification based on the final output.

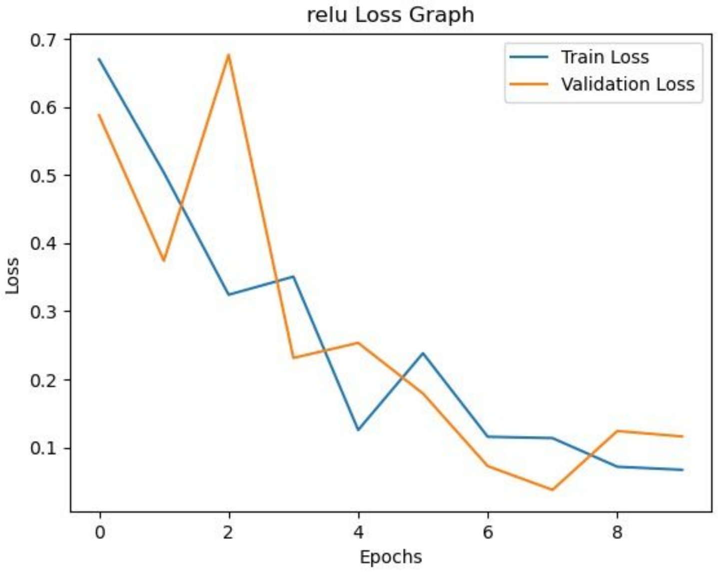
Results - CNN

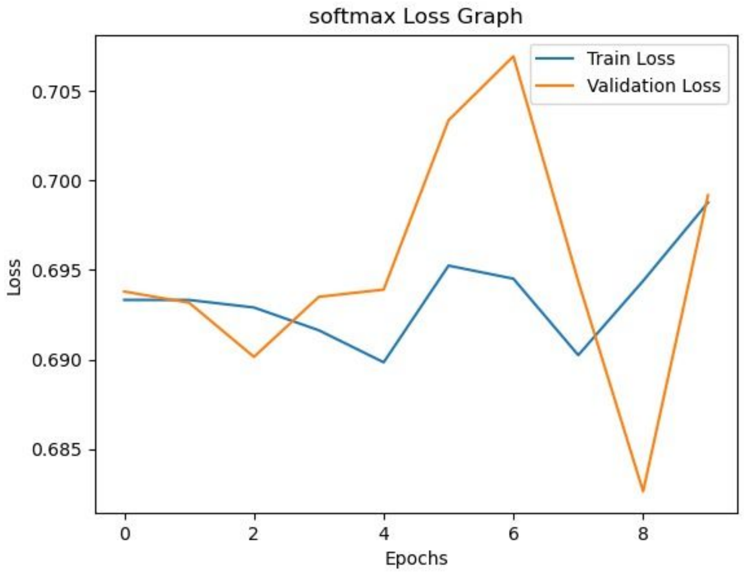

gelu Accuracy Graph
Train Accuracy
Validation Accuracy
Accuracy
Epochs


relu Accuracy Graph
Train Accuracy
Validation Accuracy
Accuracy
Epochs

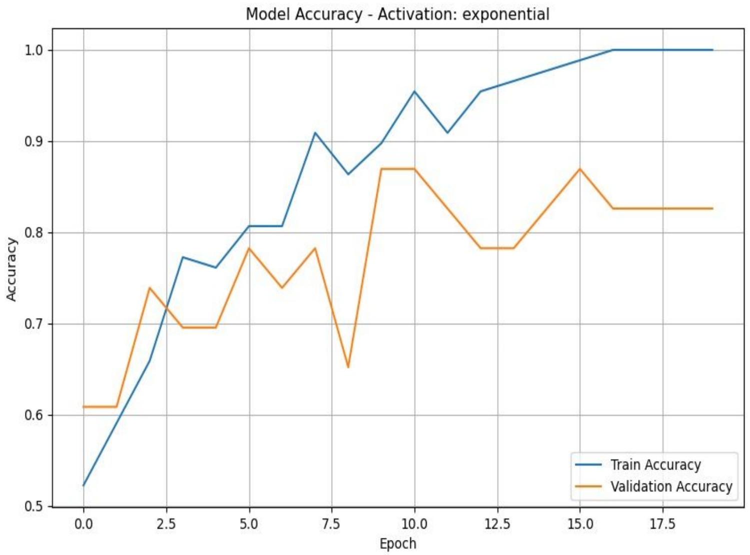

softmax Accuracy Graph
Train Accuracy
Validation Accuracy
Accuracy
Epochs

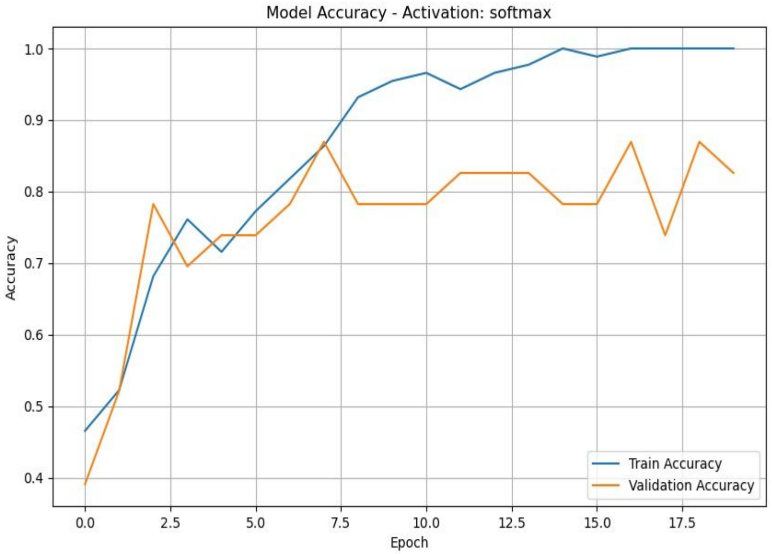

gelu Loss Graph
Train Loss
Validation Loss
Loss
Epochs

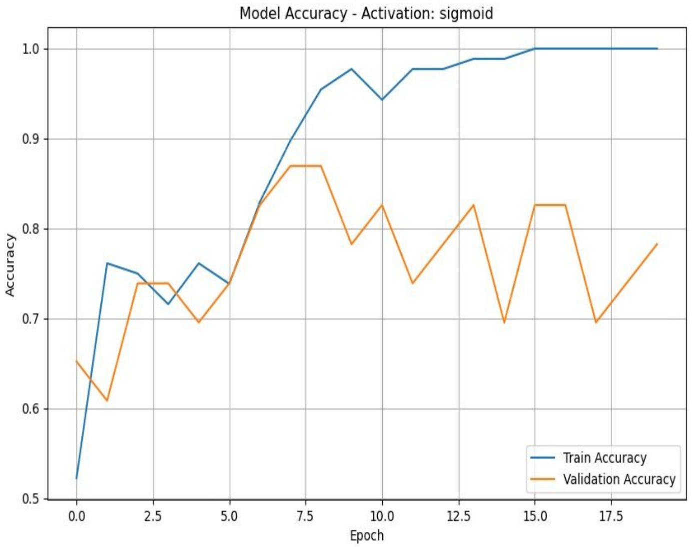

relu Loss Graph
Train Loss
Validation Loss
Loss
Epochs

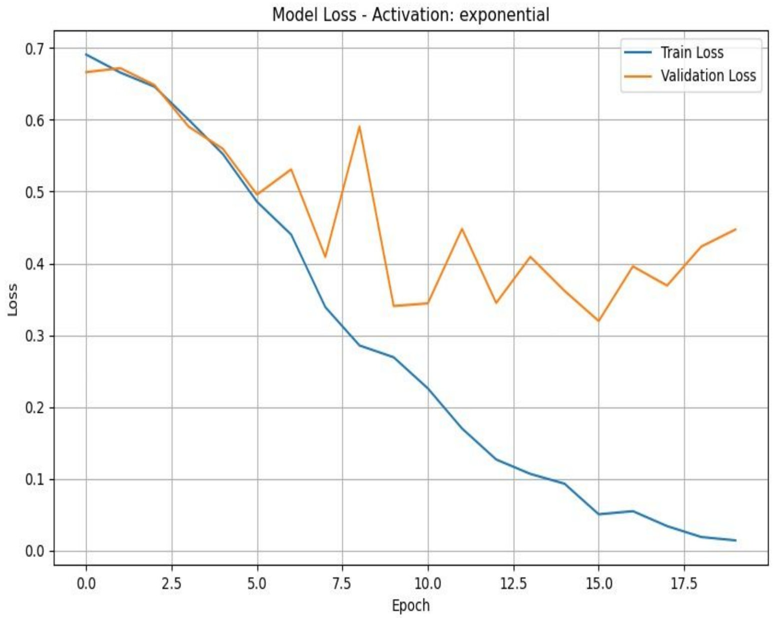

softmax Loss Graph
Train Loss
Validation Loss
Loss
Epochs

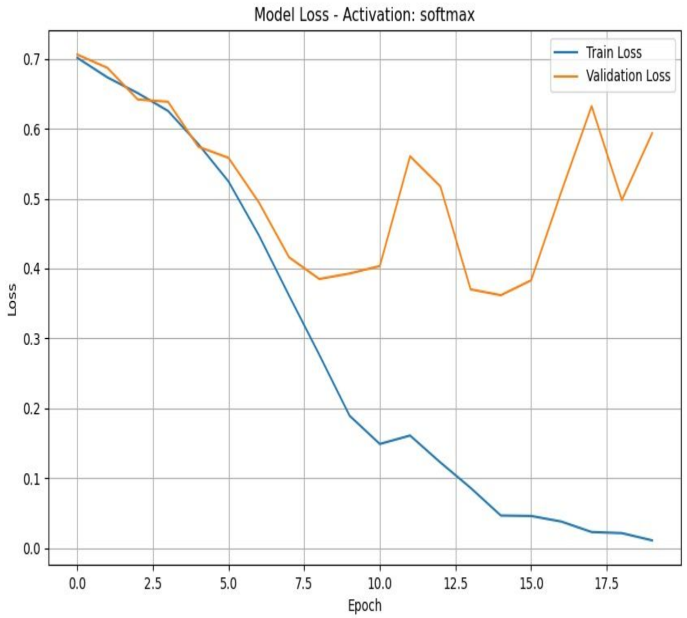
Results - LSTM

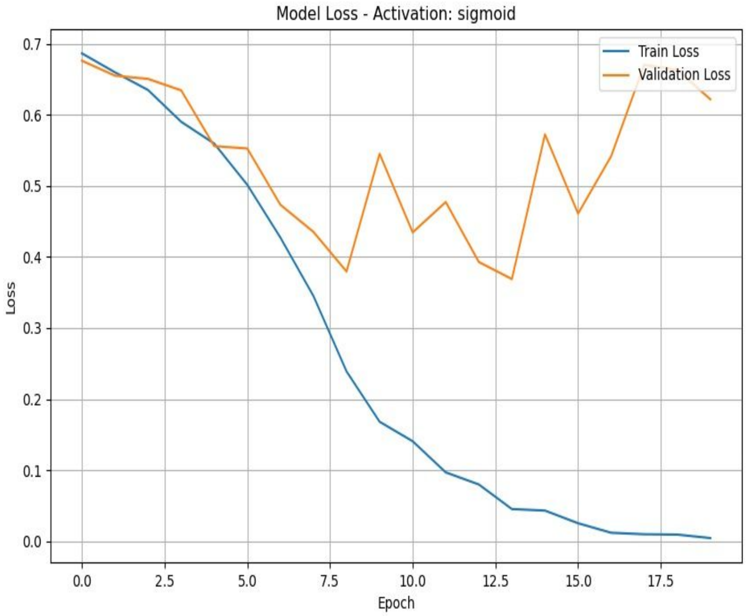












Comparison

Sr. No.	activation function	train_accuracy		val_accuracy		final_train_loss		final_val_loss	
		CNN	LSTM	CNN	LSTM	CNN	LSTM	CNN	LSTM
1	relu	0.979167	0.477273	0.96875	0.608696	0.067106	8.425368	0.116107	6.307081
2	sigmoid	0.53125	1	0.5	0.782609	2.895162	0.004532	2.968971	0.621587
3	tanh	0.927083	0.522727	0.96875	0.391304	0.173706	7.69272756576538	0.042658	9.811015
4	softmax	0.447917	1	0.4375	0.826087	0.698766	0.010882	0.699178	0.593528509140015
5	elu	0.833333	0.522727	0.84375	0.391304	0.330965	7.692727	0.263623	9.203211
6	selu	0.84375	0.522727	0.875	0.391304	0.639956	8.425368	0.618263	6.307081
7	exponential	0.53125	1	0.46875	0.826087	NA	0.013941	NA	0.447148
8	gelu	0.916667	0.613636	0.875	0.478261	0.190638	0.668827	0.353131	0.684016
9	hard_sigmoid	0.46875	0.659091	0.46875	0.521739	3.134174	0.634328	3.022728	0.676274
10	swish	0.84375	0.522727	0.96875	0.391304	0.391583	7.692728	0.187781	9.811015
11	linear	0.9375	0.522727	0.96875	0.391304	0.182637	0.695972	0.129446	0.735964

Conclusion

- ReLU and Tanh perform well in CNN, with high accuracy and low losses, making them strong choices.

- LSTM models generally show overfitting issues, particularly with sigmoid, softmax, and exponential activation functions (high training accuracy but low validation accuracy).

- GELU, Swish, and Linear show promising performance in both CNN and LSTM models, making them versatile options.

- Softmax, Exponential, and Hard Sigmoid generally perform poorly across both CNN and LSTM, suggesting they might not be suitable for this task.