# A Deep Learning Based Architecture For Differentiation Among Brain Tumor And Hemorrhage

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## ABSTRACT

Brain tumors and brain hemorrhages share overlapping characteristics, complicating the accuracy of data-driven diagnostic models. This project aims to develop a deep learning framework utilizing the VGG19 model as its backbone and incorporating an Inverted Pyramid Pooling Module (iPPM) for enhanced feature extraction. The model is designed to accurately distinguish between brain images showing tumors and hemorrhages, and is trained on a diverse dataset of CT and MRI images sourced from Kaggle and other repositories. The dataset initially comprised 4230 images of hemorrhages and 1644 images of tumors, which was expanded to 4105 images of tumors through data augmentation techniques.

## METHODOLOGY

Data Collection and Integration:

- Dataset Compilation: Combined MRI and CT images from Kaggle and various medical repositories into a unified dataset.
- Data Preprocessing: Resized all images to 256x256 pixels. Applied standard augmentation techniques: shearing, zooming (0.8 to 1.2 range), flipping, rotation (±15 degrees), brightness/contrast adjustments, grayscale conversion, Gaussian blur (7x7 kernel), and contour clipping.
- Dataset Preparation: Curated a balanced dataset with 4230 hemorrhage images and 4105 tumor images after preprocessing.

Model Architecture:

- Integrated VGG19 as the core model for robust feature extraction.
- Implemented an Inverted Pyramid Pooling Module (iPPM) with pooling sizes of 2x2, 3x3, 4x4, and 6x6 to enhance multi-scale feature extraction.
- Added two convolutional layers (128 and 256 filters) post-iPPM for feature refinement.

Model Training and Evaluation:

- Used TensorFlow and Keras. Compiled with Adam optimizer (learning rate = 0.001). Trained over epochs with early stopping. Evaluated model accuracy, achieving 99.3% on a separate test set.

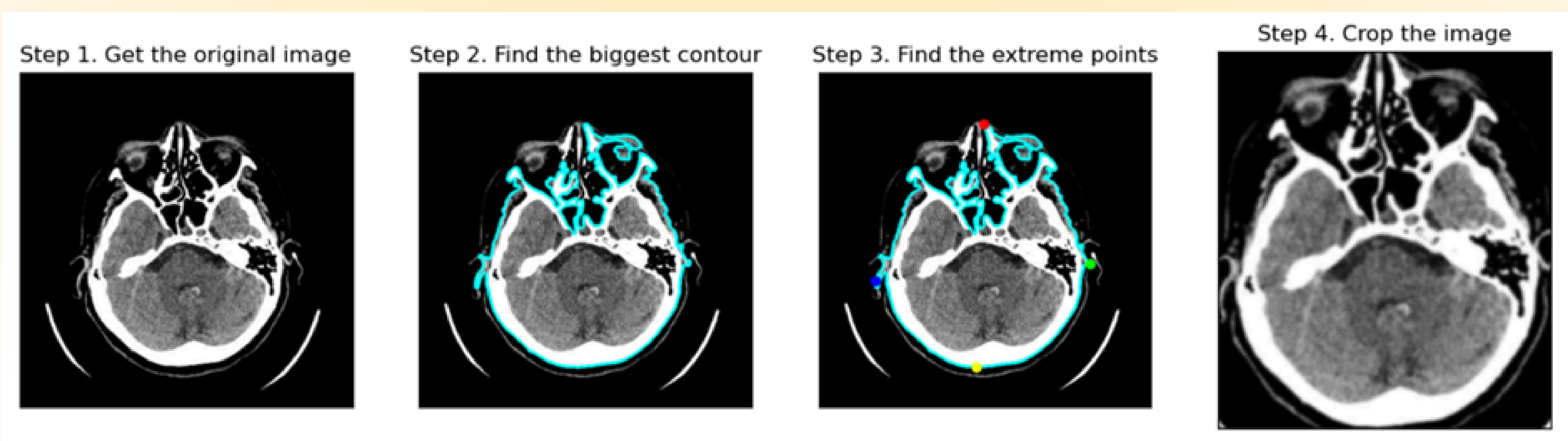


*Fig. 1 Contour Clipping*

## CONCLUSION

The multi-scale approach of the iPPM enabled NeuroNet19 to capture a comprehensive representation of the input images, improving its ability to detect subtle and varied patterns across different scales. Data augmentation techniques expanded and diversified our training set, contributing to the model's robustness and ability to generalize.

Our research highlights the potential of combining traditional image processing techniques with advanced neural network architectures to improve medical image classification.

Future work could explore the integration of additional advanced preprocessing techniques and the adaptation of the model to other medical imaging modalities.

## References

Scan The QR Code!

## MODEL ARCHITECTURE

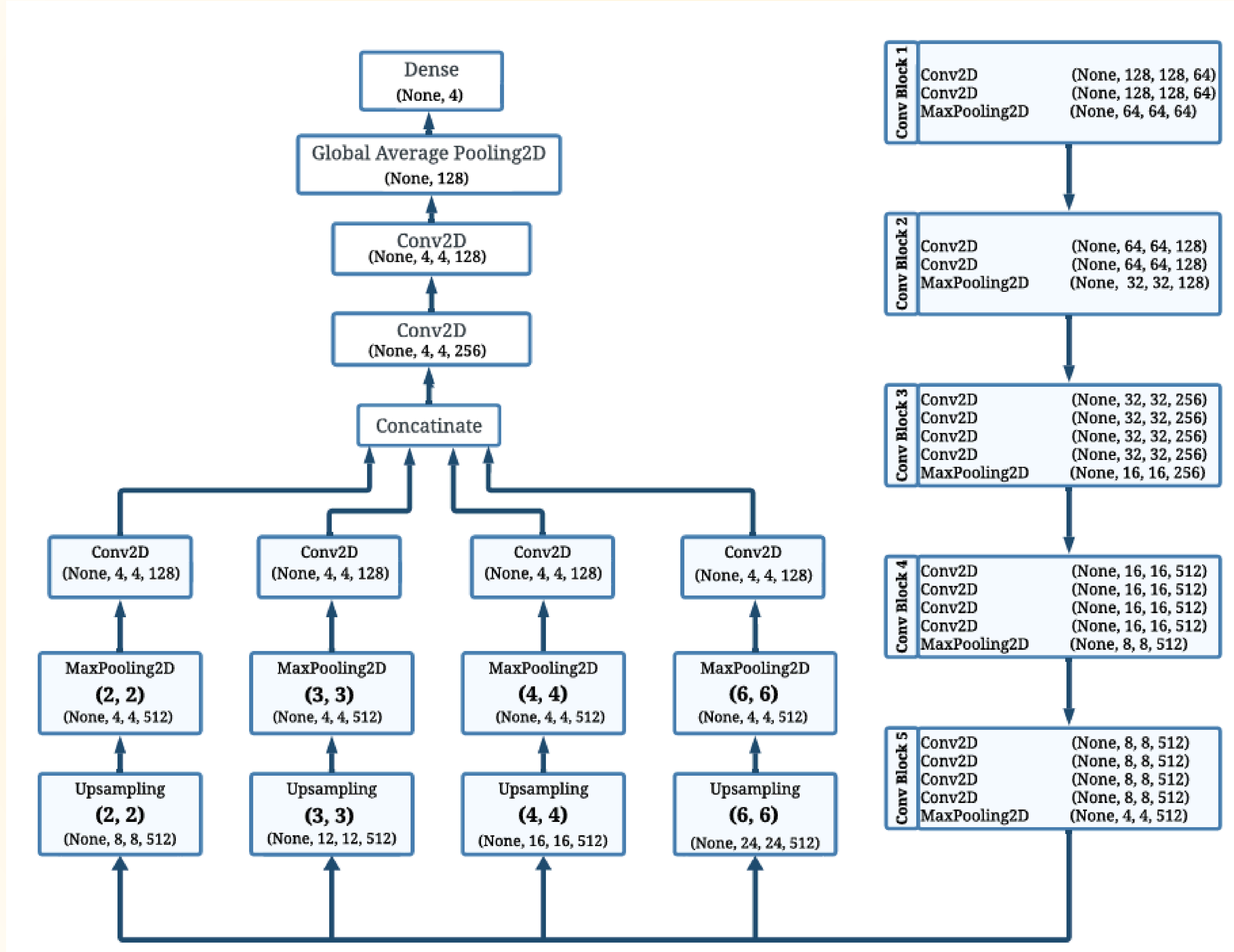


*Fig. 2 Model Architecture*

## RESULTS

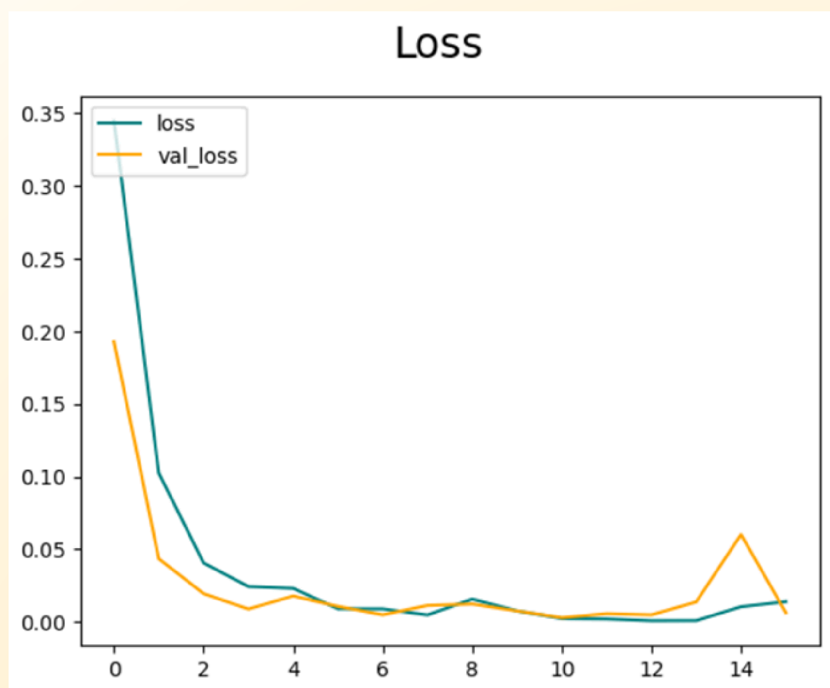


*Fig. 3 Loss*

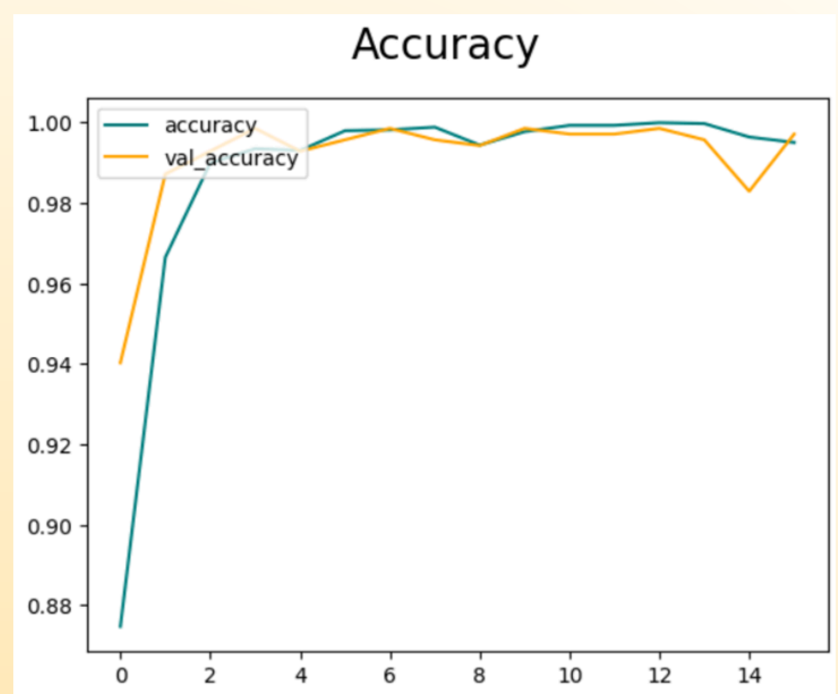


*Fig. 4 Accuracy*

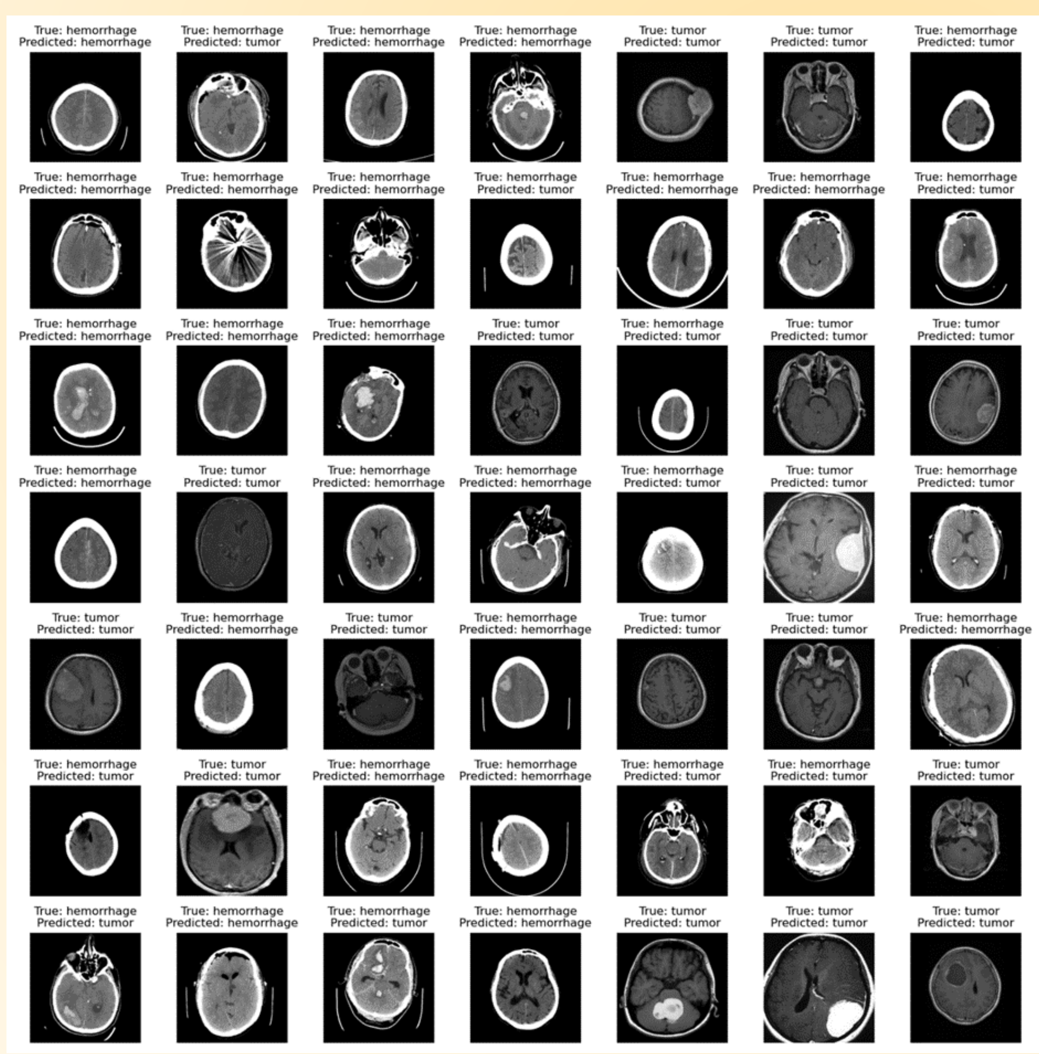

*Fig. 5 Test Images*

*Fig. 6 Performance Matrix*

| | Model | Precision | Recall | Accuracy | F1 Score |
|---|---|---|---|---|---|
| 0 | CNN (8 layers) | 0.937729 | 0.859060 | 0.916193 | 0.896673 |
| 1 | VGG16 | 0.981779 | 0.963197 | 0.976103 | 0.972399 |
| 2 | VGG19 | 0.967497 | 0.955080 | 0.966912 | 0.961249 |
| 3 | **NeuroNet19** | **0.994825** | **0.992631** | **0.993978** | **0.993727** |