A Study on Tri-Classification of ALS Pathological Images Based on Transfer Learning and Attention Mechanisms

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ALS

Introduction

- **Amyotrophic lateral sclerosis** (ALS) is a neurodegenerative disease that leads to the loss of voluntary movement and eventual death due to respiratory failure[1].
- In **non-demented ALS patients**, while TDP-43 protein accumulation is observed in all extramotor regions, not all exhibit cognitive impairments[2].
- This study seeks to unravel the intricate link between non-demented ALS patients' **cognitive impairments and their TDP-43 protein deposition**.
- Despite **deep learning**'s advancements in medical imaging and disease characterization, the exploration of its ability to delineate specific pathological markers like TDP-43 in ALS, particularly in relation **to cognitive function**, remains in its infancy.[3]
- This project harnesses **transfer learning and attention mechanisms** to address this gap.

Image Dataset

190 postmortem brain images from Aberdeen University are divided into three groups:

- **Control Group:** 70 images from individuals without ALS.
- **Concordant Group:** 60 images from ALS patients with both extramotor cortical TDP-43 pathology and cognitive impairment.
- **Discordant Group:** 60 images from ALS patients with extramotor cortical TDP-43 pathology but no cognitive impairment.

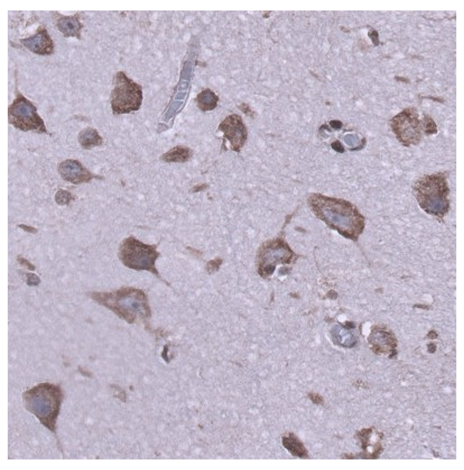


Figure1:Control

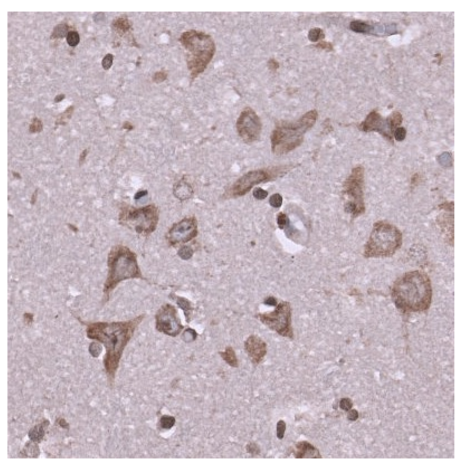


Figure2:Concordant

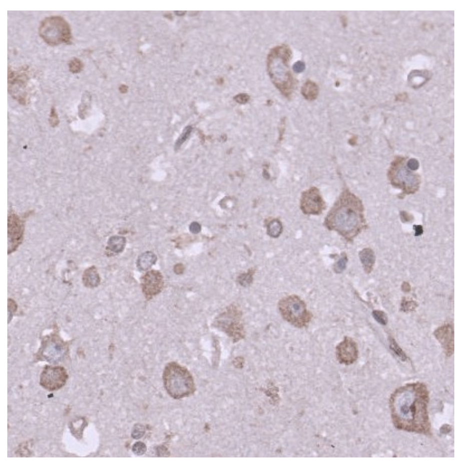
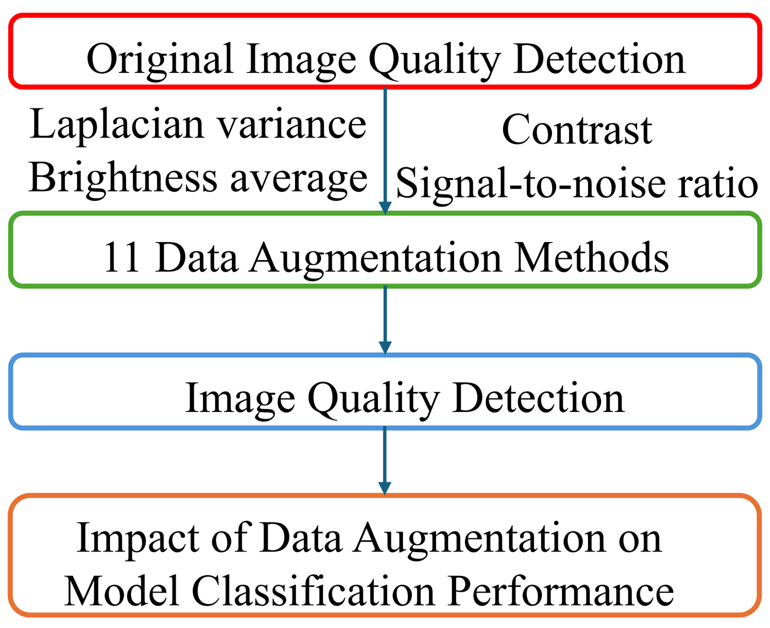
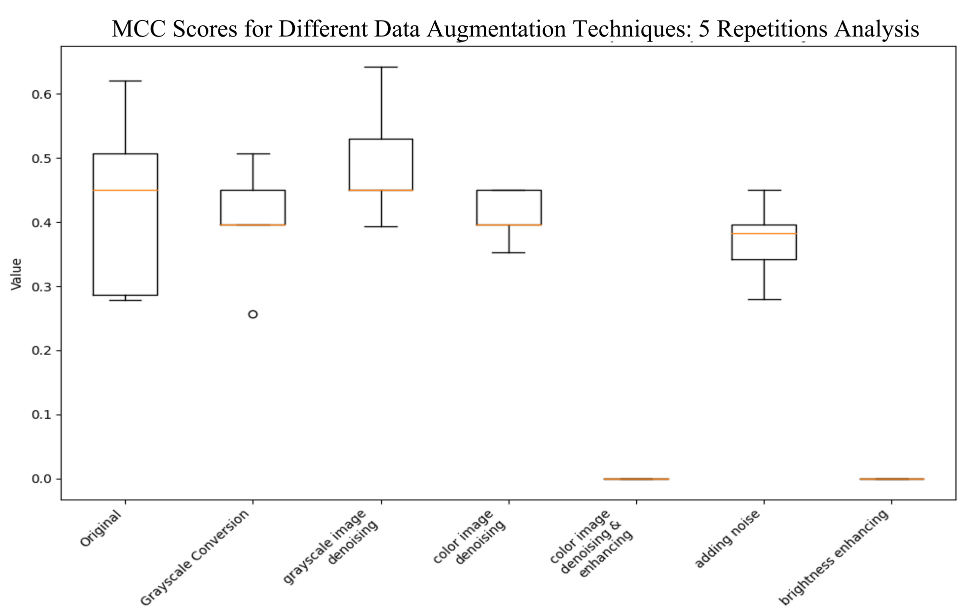


Figure3: Discordant

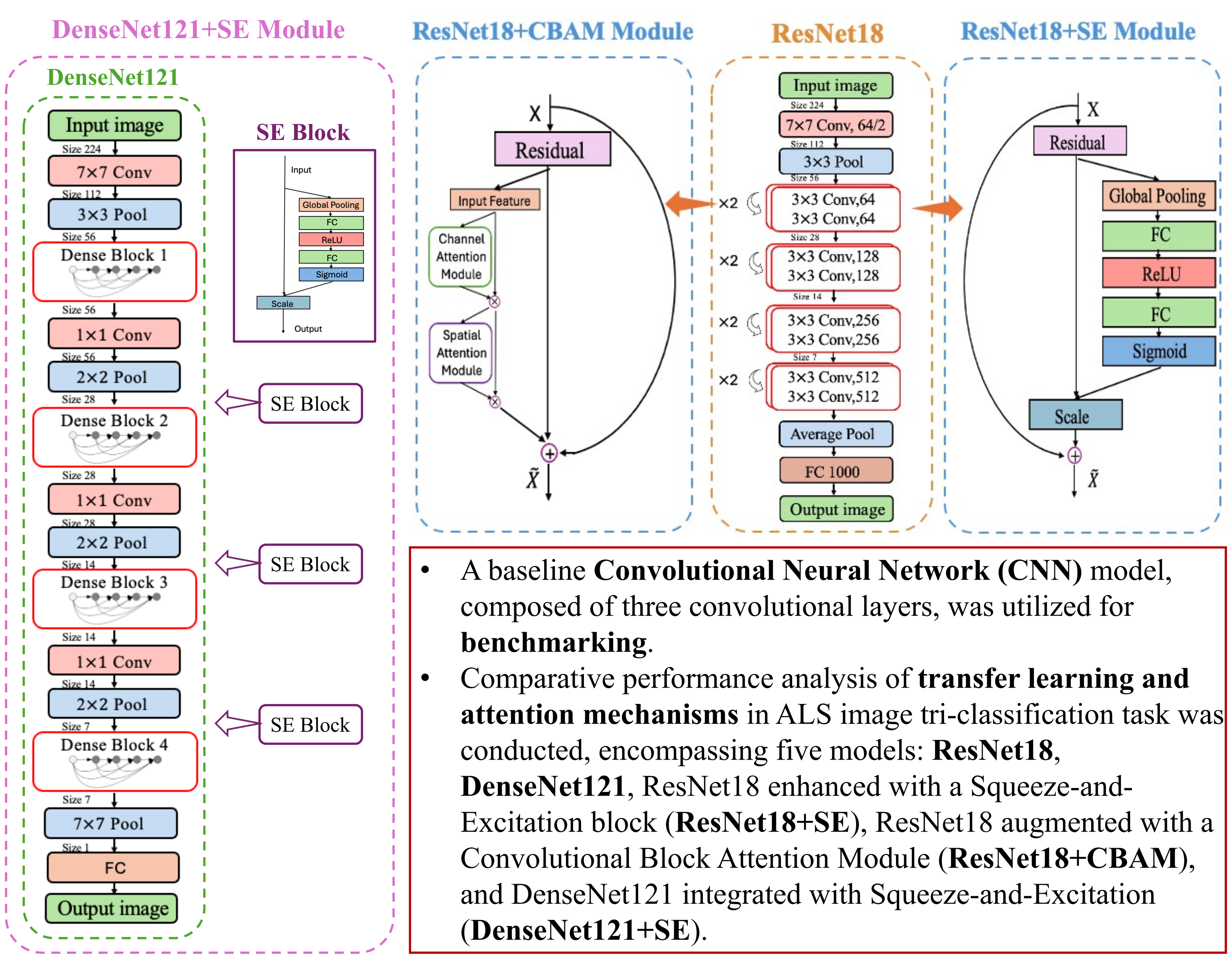




- This study will not use the two data augmentation techniques of color image denoising & enhancement and brightness enhancement, but choose to use nine other techniques.

Methodology

- The 190 images dataset was partitioned into training, validation, and test sets following a **6:2:2 allocation ratio**, with data augmentation techniques applied to enhance the training set's diversity.

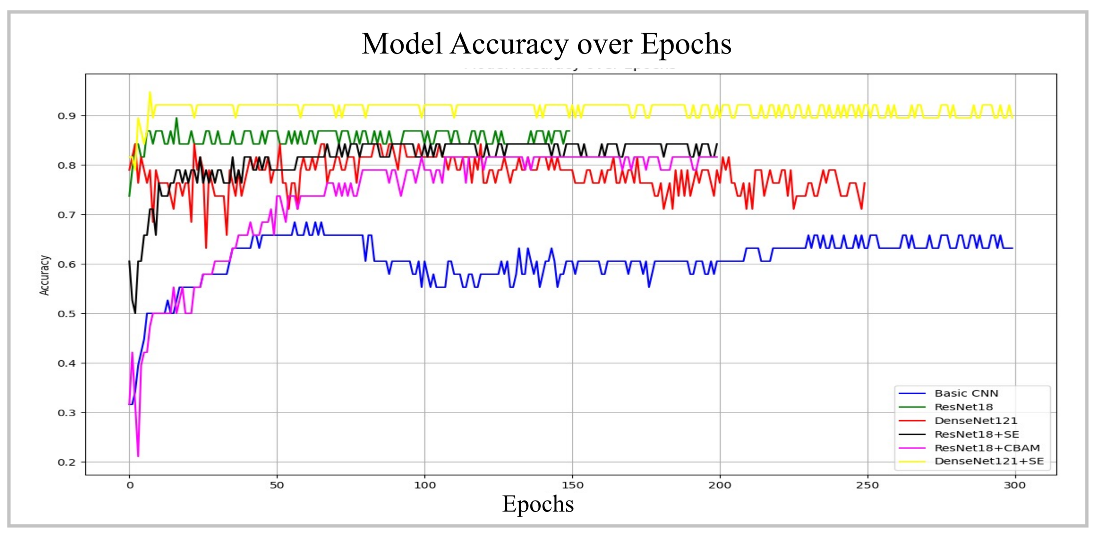


- A baseline **Convolutional Neural Network (CNN)** model, composed of three convolutional layers, was utilized for **benchmarking**.
- Comparative performance analysis of **transfer learning and attention mechanisms** in ALS image tri-classification task was conducted, encompassing five models: **ResNet18**, **DenseNet121**, ResNet18 enhanced with a Squeeze-and-Excitation block (**ResNet18+SE**), ResNet18 augmented with a Convolutional Block Attention Module (**ResNet18+CBAM**), and DenseNet121 integrated with Squeeze-and-Excitation (**DenseNet121+SE**).

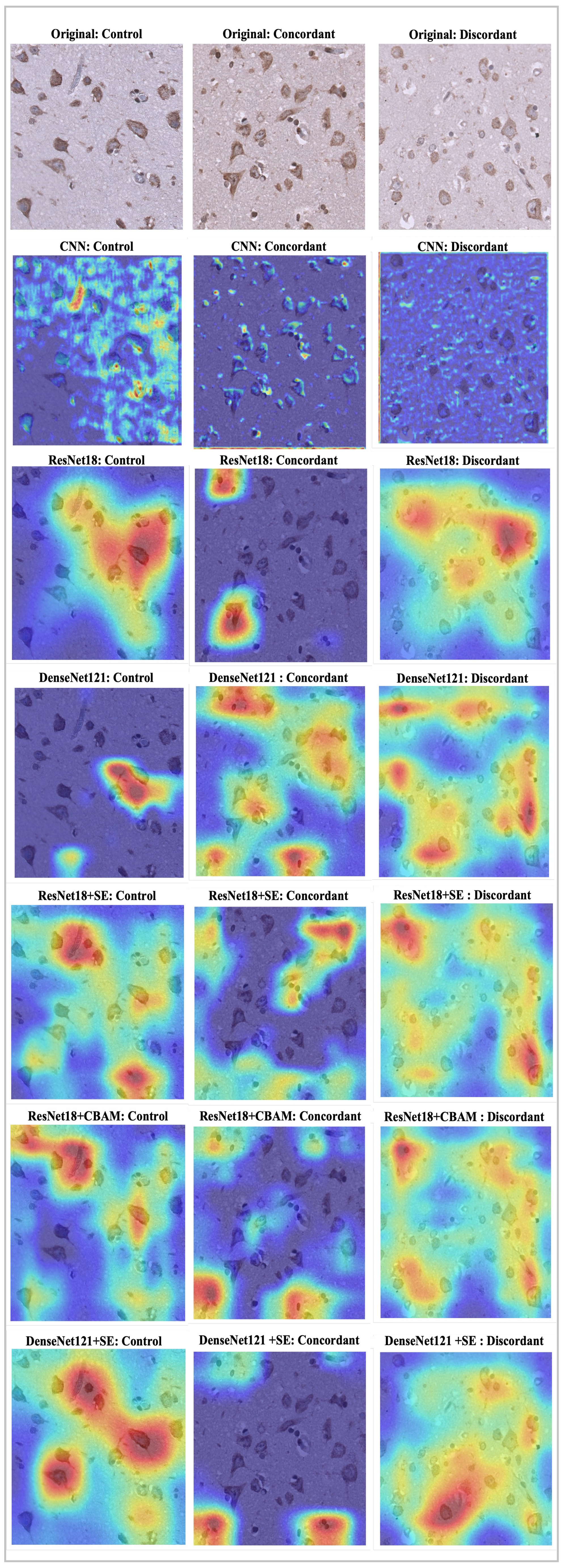
[1]. Tan, R. H., Ke, Y. D., Ittner, L. M., & Halliday, G. M. (2017). ALS/FTLD:experimental models and reality. Acta neuropathologica, 133(2), 177-196.
[2]. Gregory, Jenna M., et al. "Executive, language and fluency dysfunction are markers of localised TDP-43 cerebral pathology in non-demented ALS." *Journal of Neurology, Neurosurgery & Psychiatry* 91.2 (2020): 149-157.
[3]. Chaki, J., & Woźniak, M. (2023). Deep learning for neurodegenerative disorder (2016 to 2022): A systematic review. Biomedical Signal Processing and Control, 80, 104223.
[4]. Zhou Q, Zhou Z, Chen C, et al. Grading of hepatocellular carcinoma using 3D SE-DenseNet in dynamic enhanced MR images[J]. Computers in biology and medicine, 2019, 107: 47-57.

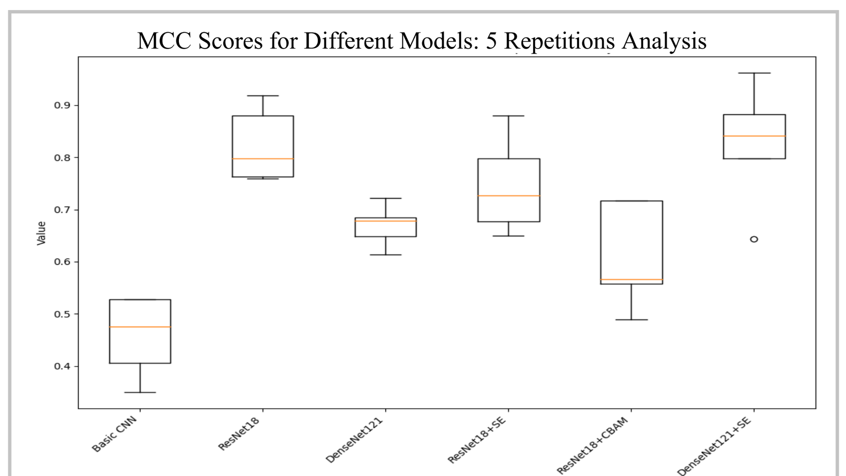
Results & Discussion

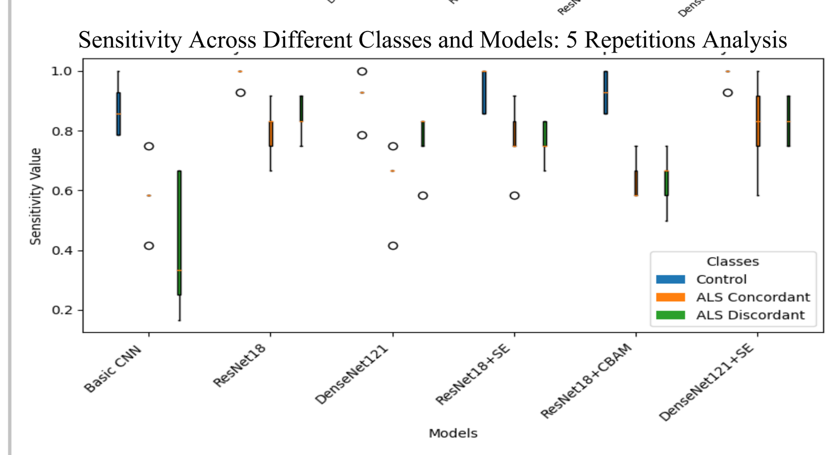
- Model performance was quantified by assessing a suite of metrics, with each trained model subjected to **five independent tests**. Evaluative criteria included **the Matthews Correlation Coefficient (MCC), accuracy, sensitivity, and specificity**.
- Gradient-weighted Class Activation Mapping (Grad-CAM) was utilized to offer a **visual interpretation** of the model's classification decisions.

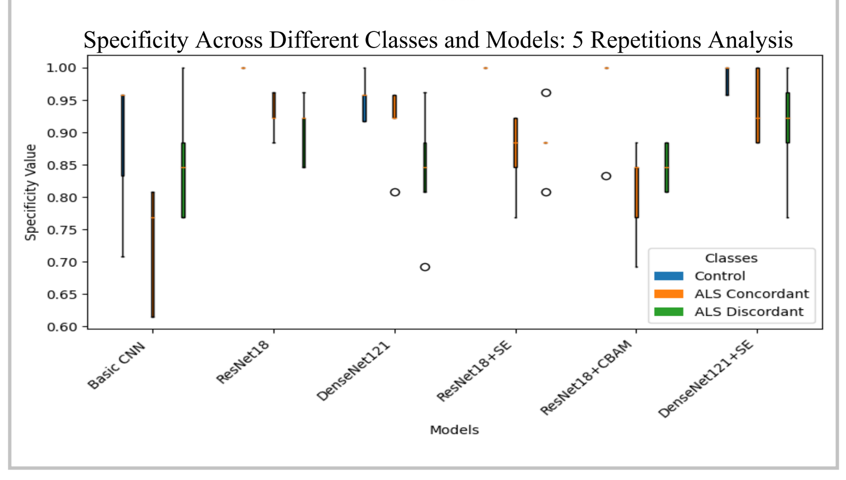


- The accuracy of the five models significantly surpassed that of conventional CNN methodologies.
- The DenseNet121+SE model demonstrated exemplary performance, **consistently achieving an accuracy rate exceeding 90%, with a peak performance of 97.37%**.









- For the **DenseNet121+SE** model, **sensitivity** and **specificity** in concordant and discordant categories reached approximately **80%** and **93%**, respectively.
- **The control group** displayed excellent sensitivity and specificity, **often reaching 1**, due to clear distinctions from ALS-affected groups. However, **concordant and discordant categories** showed lower metrics, raising questions about their stability in classification.
- Although the ResNet18 model outperformed DenseNet121, **the integration of the SE module led to a significant increase in performance for the DenseNet121+SE model**. Contrarily, the ResNet18+SE model did not fare as well.
- The SE module, by **adjusting channel importance**, boosts DenseNet121's **efficiency in feature utilization**, enhancing detection and use of key features[4].

Conclusion

- **Model Overfitting**: A majority of models exhibited overfitting, indicating the necessity for an expanded dataset to refine the models' diagnostic precision.
- **Attention Mechanism Adaptability**: The efficacy of attention mechanisms is not universally applicable across diverse architectures; their implementation demands customization to the unique characteristics of each model.
- **Model Interpretability and Validation**: Despite efforts to visualize and comprehend the internal workings of the models, further endeavors are essential, including validation of the models' focal points with medical professionals to ensure accuracy.
- **Future Directions**: Enhancing the DenseNet+SE model for greater ALS diagnostic accuracy emerges as a primary research avenue. Further exploration into combining imaging with genetic and clinical data, and refining attention mechanisms for neurodegenerative disease specifics, also present promising paths.