CONCLUSION

In conclusion, the utilization of Transformer-based methodologies has significantly enhanced the performance of multi-label retinal disease classification, particularly when compared to traditional Convolutional Neural Network (CNN) approaches. Through the analysis of the MuReD dataset, it has become evident that the Transformer architecture, with its inherent self-attention mechanism, surpasses the capabilities of CNN-based models in capturing intricate relationships within the data.

One of the notable advantages of the Transformer architecture lies in its attention visualization capabilities, which offer profound insights into the decision-making process of the model. By visualizing the attention maps, we gain a deeper understanding of the specific features and patterns guiding the model's predictions, thereby facilitating interpretability and trust in the model's outputs.

Moreover, our Transformer-based model has demonstrated remarkable efficacy in learning complex dependencies between labels and features, achieving an impressive ML_AUC score of 0.927 on the MuReD dataset. This achievement underscores the Transformer's ability to effectively capture and leverage the intricate relationships inherent in multi-label classification tasks, ultimately leading to superior predictive performance.

Moving forward, the success of Transformer-based approaches in multi-label retinal disease classification paves the way for further exploration and application of these methodologies in other medical imaging tasks. The scalability and adaptability of the Transformer architecture position it as a promising candidate for addressing various challenges across diverse domains, thereby contributing to advancements in healthcare diagnostics and beyond.

In summary, our study highlights the transformative potential of Transformer-based models in revolutionizing the field of medical image analysis, offering unparalleled performance, interpretability, and scalability. As we continue to delve deeper into the capabilities of these architectures.

RESULT

Displayed below is the final Area Under the Curve (AUC) metric obtained from our model evaluation process.

The attained AUC value serves as a pivotal indicator of our model's discriminative ability and overall performance in multi-label retinal disease classification. With meticulous analysis and optimization, our model achieved a commendable AUC score, reflecting its capacity for accurate and reliable prediction across various disease categories. This result underscores the efficacy of our approach and its potential for enhancing diagnostic precision in clinical settings.

```
80/80 [==============================] - 156s 2s/step - loss: 0.1670 - accuracy: 0.4422 - auc: 0.8735 - val_loss: 0.1701 - val_accuracy: 0.4375 - val_auc: 0.8591
Epoch 8/20
80/80 [==============================] - 154s 2s/step - loss: 0.1606 - accuracy: 0.4664 - auc: 0.8834 - val_loss: 0.1561 - val_accuracy: 0.5281 - val_auc: 0.8914
Epoch 9/20
80/80 [==============================] - 154s 2s/step - loss: 0.1556 - accuracy: 0.4625 - auc: 0.8954 - val_loss: 0.1444 - val_accuracy: 0.5344 - val_auc: 0.9084
Epoch 10/20
80/80 [==============================] - 169s 2s/step - loss: 0.1466 - accuracy: 0.4930 - auc: 0.9114 - val_loss: 0.1485 - val_accuracy: 0.5125 - val_auc: 0.9022
Epoch 11/20
80/80 [==============================] - 158s 2s/step - loss: 0.1413 - accuracy: 0.5180 - auc: 0.9178 - val_loss: 0.1480 - val_accuracy: 0.4719 - val_auc: 0.9086
Epoch 12/20
80/80 [==============================] - 157s 2s/step - loss: 0.1346 - accuracy: 0.5422 - auc: 0.9284 - val_loss: 0.1388 - val_accuracy: 0.5312 - val_auc: 0.9151
Epoch 13/20
80/80 [==============================] - 160s 2s/step - loss: 0.1355 - accuracy: 0.5398 - auc: 0.9234 - val_loss: 0.1660 - val_accuracy: 0.4625 - val_auc: 0.8989
Epoch 14/20
80/80 [==============================] - 156s 2s/step - loss: 0.1310 - accuracy: 0.5664 - auc: 0.9303 - val_loss: 0.1386 - val_accuracy: 0.5312 - val_auc: 0.9230
Epoch 15/20
80/80 [==============================] - 155s 2s/step - loss: 0.1209 - accuracy: 0.5906 - auc: 0.9419 - val_loss: 0.1641 - val_accuracy: 0.4906 - val_auc: 0.8956
Epoch 16/20
80/80 [==============================] - 152s 2s/step - loss: 0.1203 - accuracy: 0.6039 - auc: 0.9427 - val_loss: 0.1458 - val_accuracy: 0.5031 - val_auc: 0.9114
Epoch 17/20
80/80 [==============================] - 153s 2s/step - loss: 0.1165 - accuracy: 0.6102 - auc: 0.9485 - val_loss: 0.1318 - val_accuracy: 0.5750 - val_auc: 0.9254
Epoch 18/20
80/80 [==============================] - 153s 2s/step - loss: 0.1101 - accuracy: 0.6313 - auc: 0.9530 - val_loss: 0.1449 - val_accuracy: 0.5469 - val_auc: 0.9187
Epoch 19/20
80/80 [==============================] - 155s 2s/step - loss: 0.1134 - accuracy: 0.6133 - auc: 0.9508 - val_loss: 0.1548 - val_accuracy: 0.4750 - val_auc: 0.9074
Epoch 20/20
80/80 [==============================] - 154s 2s/step - loss: 0.1095 - accuracy: 0.6359 - auc: 0.9558 - val_loss: 0.1335 - val_accuracy: 0.5813 - val_auc: 0.9273
```

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