Findings and Conclusion

The Random Forest model achieved an accuracy of 95.83%, with a weighted average F1 score of 96% before and after tuning. This indicates that the model performed exceptionally well in correctly predicting the classes across the dataset, handling class imbalance effectively. The stability of these metrics post-tuning suggests that the initial model configuration was already close to optimal. The Random Forest model exhibited the highest performance in comparison with other models, both before and after tuning. This superior performance can be attributed to the ensemble nature of Random Forests, which effectively reduces overfitting and handles class imbalance through class weights.

The MLP model demonstrated an accuracy of 83.33%, with a weighted average F1 score of 85% after tuning slightly higher than the pre-tuning. This suggests that the model was able to capture and generalize patterns from the data reasonably well, even before detailed tuning. This consistency indicates that the pre-tuned model was already well-optimized and that the hyperparameters were effectively set. The CNN model achieved an accuracy of 85%, with a weighted average F1 score of 87% after tuning about 2% above the metrics before tuning. This performance reflects the model's ability to learn complex features from the data, leveraging convolutional layers. This indicates that the initial model configuration was robust, and the tuning process confirmed the effectiveness of the chosen hyperparameters. The MLP and CNN models displayed similar performances, with an accuracy of 83.33% and 85% and weighted average F1 scores of 85% and 87% respectively. The inclusion of SMOTE for data balancing and class weights improved their handling of class imbalance, resulting in stable performance before and after tuning. The similarity in performance between MLP and CNN suggests that both models are capable of learning complex patterns in the data, though neither outperformed the Random Forest.

The K-means clustering algorithm initially showed an accuracy of 79% with a weighted average F1 score of 75%. This reflects a moderate alignment between the clusters and the actual classes, though there were significant misclassifications. After tuning, the performance of K-means clustering decreased, resulting in an accuracy of 59% and a weighted average F1 score of 47%. The reduction in these metrics highlights the challenges in fine-tuning an unsupervised method to align well with labelled data. The K-means clustering algorithm performed the least effectively, and this is expected as clustering is unsupervised, and aligning clusters with actual classes remains challenging without label information. The reduced performance after tuning may indicate difficulty in finding a clustering configuration that aligns well with the true class distribution.

In conclusion, the Random Forest model's robustness and capacity to handle imbalanced data make it the most effective model for this task, followed by the MLP and CNN models which also performed well. The K-means clustering model, being unsupervised, did not perform as well as the supervised models. The results highlight the importance of using supervised learning techniques and appropriate data preprocessing methods, such as SMOTE and class weights, for achieving high classification performance.