	T-C	**95%**	**95%**	**95%**	**95%**
	S-C	89%	90%	89%	89%
	T-S	76%	80%	76%	75%
	T-C-S	92%	92%	92%	92%
Logistic Regression	**T**	85%	85%	85%	85%
	C	91%	92%	91%	91%
	S	91%	91%	91%	91%
	T-C	89%	90%	89%	89%
	S-C	92%	92%	92%	92%
	T-S	92%	92%	92%	92%
	T-C-S	**94%**	**94%**	**94%**	**94%**

B. Discussion

Based on the analysis of results of each model in the Tables 4 – Tables 8, it can be seen that CNN shows outstanding performance, reaching 100% in accuracy, precision, recall, and f1-score on both test and validation datasets. This indicates that the CNN in the model in this study excels in feature extraction and has a remarkable capacity for generalization to new data. With no signs of overfitting or underfitting, the model is believed to be adept at learning features and generalizing to unprecedented datasets. CNN is the optimal model for this study due to its outstanding ability to identify patterns in images. In addition, CNN is clearly capable of outperforming several machine learning models, specifically SVM, Random Forest, and Logistic Regression. Despite the good results on testing machine learning models, the findings from CNN were superior.

The second method used, Ensemble Learning with Voting Classifier, significantly improved the model, especially the T-C feature combination, achieving performance results of 97% on test data and 98% on validation data in accuracy, precision, recall, and f1-score. Although there is a slight difference in the test and validation results of the ensemble model, the performance of this model is quite stable with high accuracy, so it can be said that this model also works well in this study even though its performance cannot equal the CNN results.

Conclussion

Based on the evaluation of model performance on validation and test data, the results obtained show excellent performance to address the limitations of previous research, with an accuracy range of 97% for test and 98% for validation for the ensemble learning voting classifier model and 100% for the CNN model in both test and validation. The small difference between the validation and test results indicates that the model can generalize the new data very well, without showing signs of overfitting/underfitting. The ensemble learning performance itself has not been able to outperform CNN in this study. But in general, the CNN and ensemble learning models are quite stable and able to provide accurate predictions to detect the spoofing videos. For future research, it is recommended to explore training with the latest models that are more accurate in making predictions, and consider using more alternative feature extraction methods. This can help improve the performance of the model in the face of more diverse data variations.

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