Table 4 Comparison review with existing work's methods and accuracy scores.

Method	Data set	Subject	F1 Score	Modality	Training Accuracy	Validation Accuracy
SVM EBF [18]	CASIA	75	0.890	RGB	0.90	0.89
Spoof ResNet [19]	MSU-MFSD	35	N/A	RGB	0.978	0.944
MTCNN [20]	YOUTU	3350	0.956	RGB/IR	0.962	0.978
SqueezeNet [21]	CASIA-SURF	1000	N/A	Color, Depth & IR	N/A	0.998
FusionNet	CASIA-SURF	300	**0.998**	Color, Depth & IR	**0.997**	**0.998**

4. Conclusion

In this research, we used a deep learning method focused on Fusion CNN architecture to derive facial patches and depth of 3 types of human facial image samples namely Color, Depth and IR from the CASIA-SURF dataset modeled with an altered 3D convolutional neural network classifier. Our primary interest was to be able to extract facial patches and the depth levels of all 3 facial inputs stated earlier on to distinguish a real face from a spoofed face from a CASIA-SURF dataset provided which are not preprocessed.

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