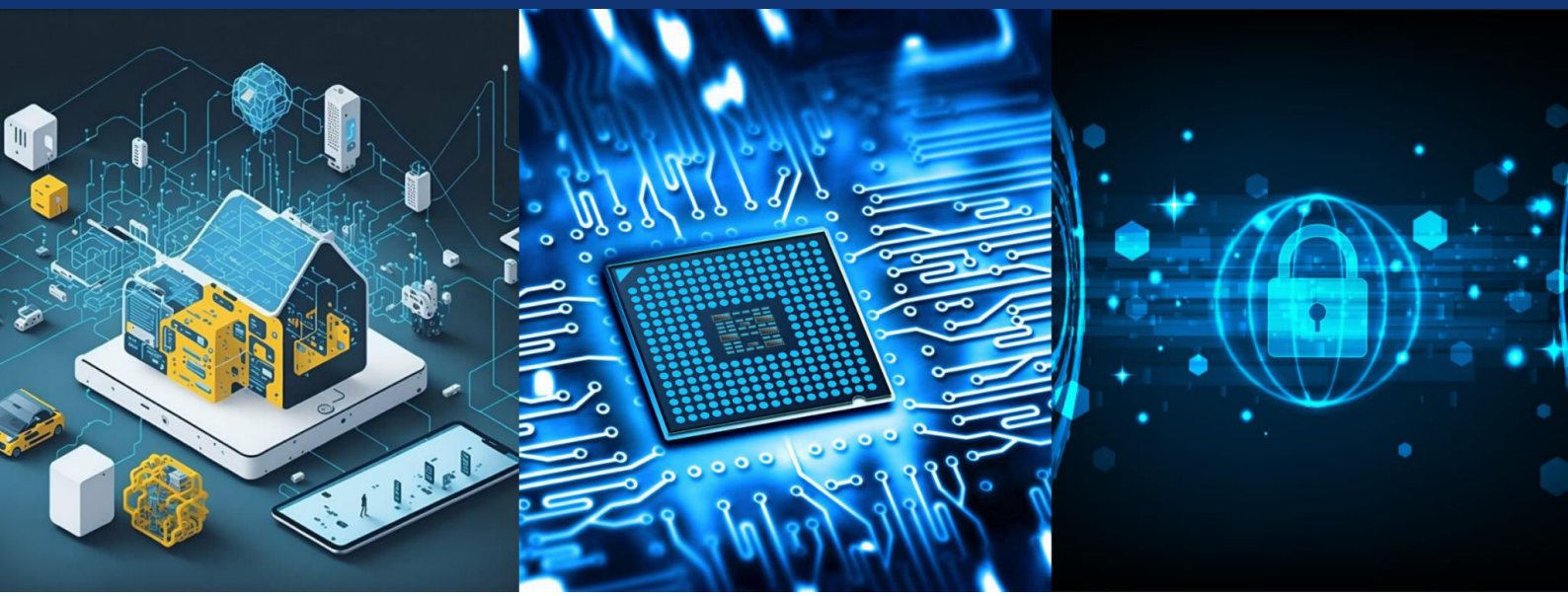
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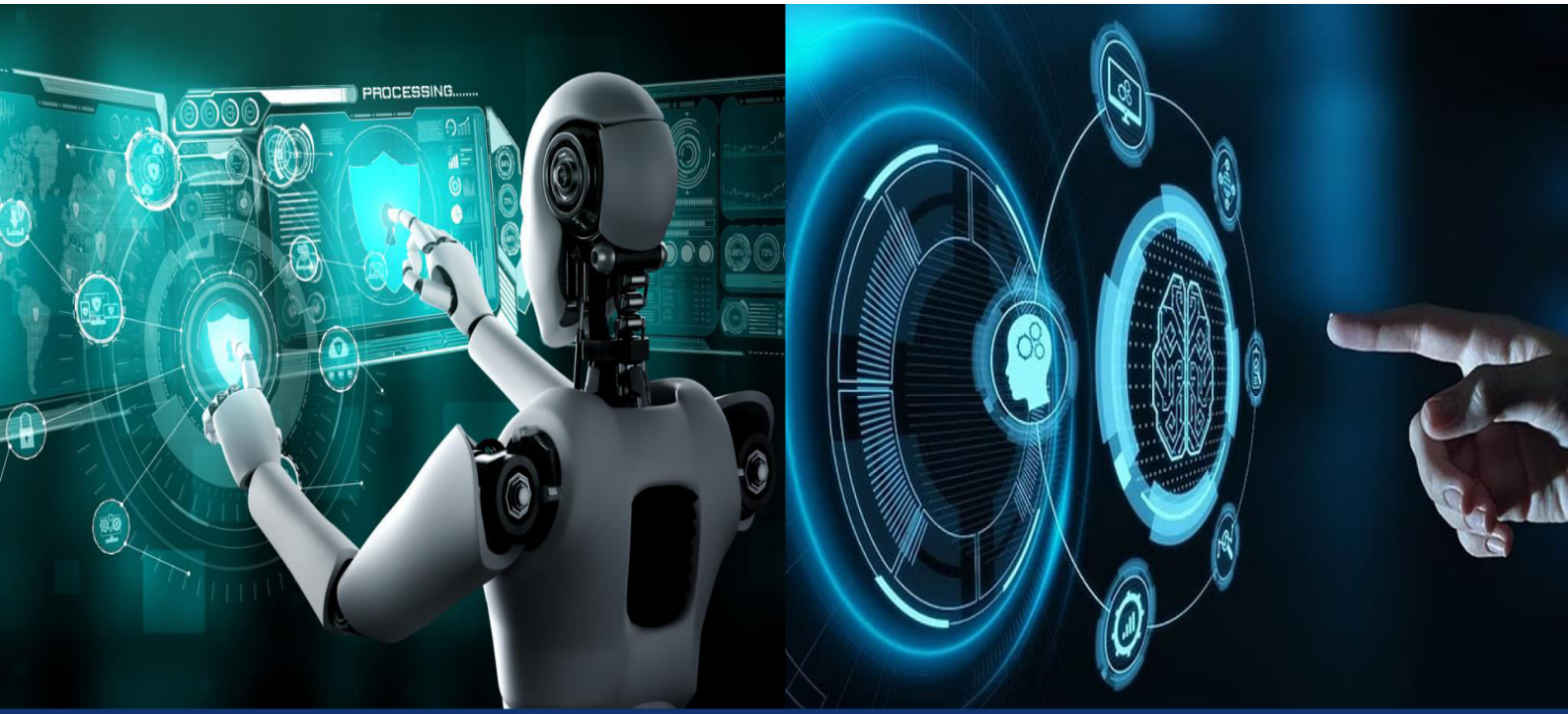
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Analysis of Thermal, Visible, and Fused Image-Based Face Recognition Using HOG-SVM

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ABSTRACT: Recognizing individuals from facial images is an important task in biometric identification. However, differences in lighting and image characteristics can influence the reliability of face recognition systems. This study investigates the performance of a Histogram of Oriented Gradients (HOG)-based feature extraction method combined with a Support Vector Machine (SVM) classifier for three types of facial images: thermal, visible, and fused. The experimental dataset contains 1,108 images representing 17 subject classes. HOG descriptors are used to represent facial edges and structural patterns, while an SVM with a Radial Basis Function (RBF) kernel assigns each image to its corresponding subject class. The recorded experimental results show classification accuracies of 46.88% for thermal images, 81.08% for visible images, and 88.75% for fused images. The fused dataset produces the highest accuracy among the three image types, with a difference of 7.67 percentage points compared with the visible dataset. These findings suggest that combining thermal and visible facial information may provide more useful features for HOG-SVM classification under the tested conditions. Further evaluation using independent datasets and repeated experiments is necessary to establish the reliability and generalizability of these results.

KEYWORDS: Facial identification, gradient-based feature extraction, support vector classification, infrared facial images, visible imagery, multimodal image fusion.

I. INTRODUCTION

Face recognition is an important biometric technology used to identify individuals based on their facial characteristics. It is widely applied in security systems, access control, surveillance, and identity verification. The accuracy of a face recognition system depends on several factors, including image quality, illumination, facial appearance, and the feature extraction technique used. Visible facial images may lose important details under poor lighting conditions. Thermal imaging provides an alternative by capturing heat patterns from the human face, which can be useful when visible-light conditions are unfavorable [13], [14].Researchers have explored thermal and visible facial images to improve the reliability of face recognition systems. Socolinsky et al. [14] investigated face recognition using visible and thermal infrared imagery. Bebis et al. [15] studied the fusion of thermal infrared and visible images, while Kong et al. [16] examined multiscale image fusion for illumination-invariant face recognition. Hermosilla et al. [17] investigated the fusion of thermal and visible descriptors. These studies provide a foundation for examining how different image modalities and fusion techniques influence recognition performance.Feature extraction is a major step in machine-learning-based face recognition. Histogram of Oriented Gradients (HOG) is a feature descriptor that represents local image structure by calculating the distribution of gradient orientations. Dalal and Triggs [18] introduced HOG for human detection, and Déniz et al. [19] investigated its application to face recognition. HOG can represent facial edges and structural patterns without requiring a deep neural network to learn the features directly from the training data.Support Vector Machine (SVM) is a supervised machine-learning algorithm used to classify data by identifying suitable decision boundaries between classes. Cortes and Vapnik [20] introduced support-vector networks, which form the theoretical basis of SVM classification. An SVM can use different kernel functions to handle classification problems with complex feature distributions. In this study, the Radial Basis Function (RBF) kernel is used to classify facial images based on their extracted HOG features.Previous research has also examined thermal face recognition using other feature extraction and learning approaches.

Gadekar et al. [11] studied thermal face recognition using Principal Component Analysis (PCA), while Mali et al. [12] reviewed a simplified Convolutional Neural Network approach for thermal face recognition. These studies highlight continuing interest in developing recognition methods suitable for thermal facial images.Although thermal, visible, and fused face recognition have been investigated in earlier studies, it remains important to evaluate a common

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classification approach across these image modalities. Differences in image characteristics and feature quality may influence the final recognition accuracy. Therefore, this study investigates HOG-based feature extraction combined with an SVM classifier for thermal, visible, and fused facial images.The dataset used in this work contains 1,108 images distributed across 17 subject classes. HOG descriptors are extracted from the facial images, and an SVM with an RBF kernel is trained to classify the subjects. The performance of the proposed HOG-SVM approach is evaluated separately for thermal, visible, and fused datasets. The recorded accuracies are 46.88%, 81.08%, and 88.75%, respectively.The main contribution of this study is a comparative evaluation of HOG-SVM across three facial image modalities under the implemented experimental settings. The results help identify the modality that performs best with this approach and provide a basis for further investigation using larger datasets, alternative feature descriptors, and additional classification methods.

II. LITERATURE REVIEW

Research on face recognition has explored different image modalities, feature extraction techniques, and classification algorithms. Thermal imaging, visible imaging, and image fusion have received attention because each modality provides different information about facial characteristics. This section reviews studies related to thermal face recognition, multimodal image fusion, HOG feature extraction, SVM classification, and the author's previous research.Socolinsky et al. [14] investigated face recognition using visible and thermal infrared imagery. Their work examined the use of different imaging modalities for facial identification. Bebis et al. [15] studied face recognition by combining thermal infrared and visible images. Their research highlighted the potential of image fusion for improving recognition performance. Similarly, Kong et al. [16] proposed multiscale fusion of visible and thermal infrared images to support illumination-invariant face recognition. Hermosilla et al. [17] investigated the fusion of thermal and visible descriptors using genetic algorithms. These studies provide a foundation for evaluating fused facial images alongside individual thermal and visible modalities.

Ghiass et al. [13] presented a comprehensive review of infrared face recognition methodologies and databases. Their review discussed different approaches to thermal face recognition and the challenges associated with infrared facial imagery. This work is relevant to the present study because it establishes the importance of evaluating thermal imaging techniques and their suitability for recognition tasks.

Dalal and Triggs [18] introduced Histograms of Oriented Gradients (HOG) for human detection. The descriptor represents local image structures by measuring gradient orientations within image regions. Déniz et al. [19] subsequently investigated HOG for face recognition, demonstrating the relevance of gradient-based features to facial image analysis. HOG is therefore considered in this study as a handcrafted feature extraction method for representing facial structure.Cortes and Vapnik [20] introduced Support Vector Networks, which form the foundation of Support Vector Machine (SVM) classification. SVMs identify decision boundaries that separate data belonging to different classes. Kernel functions allow SVMs to classify data with nonlinear feature distributions. In the present work, an SVM with a Radial Basis Function (RBF) kernel is combined with HOG descriptors to classify facial images into subject classes.Related studies have also investigated alternative approaches to thermal face recognition. Gadekar et al. [11] studied Principal Component Analysis (PCA) for thermal face recognition, while Mali et al. [12] reviewed a simplified Convolutional Neural Network (CNN) approach for thermal face recognition tasks. These publications provide background for the continued investigation of feature representation and classification methods for thermal facial images. The current study differs by experimentally evaluating a HOG-SVM approach across thermal, visible, and fused image datasets.Based on the reviewed literature, thermal and visible image fusion, gradient-based feature extraction, and supervised classification are relevant directions for face recognition research. However, recognition performance depends on the selected dataset, image modality, feature representation, and experimental settings. Therefore, this study evaluates HOG-SVM using three facial image modalities containing 1,108 images from 17 subject classes. The recorded accuracies are compared to determine which modality performs best under the implemented experimental condition.

III. PROPOSED METHODOLOGY

The proposed method uses Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machine (SVM) for face classification. The dataset contains 1,108 facial images divided into three modalities: thermal, visible, and fused images, representing 17 subject classes.

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First, the images are loaded and preprocessed to maintain a consistent input format. HOG descriptors are then extracted to represent facial edges and gradient patterns. The extracted features are divided into training and testing sets using an 80:20 split. An SVM classifier with a Radial Basis Function (RBF) kernel is trained using the training features and their corresponding subject labels. Finally, the trained model predicts the classes of test images, and recognition accuracy is calculated separately for thermal, visible, and fused datasets.The recorded accuracies are 46.88% for thermal images, 81.08% for visible images, and 88.75% for fused images. The results are compared to determine the performance of HOG-SVM across the three image modalities.

Proposed workflow

Figure 1. System flow of the proposed HOG-SVM face recognition method.

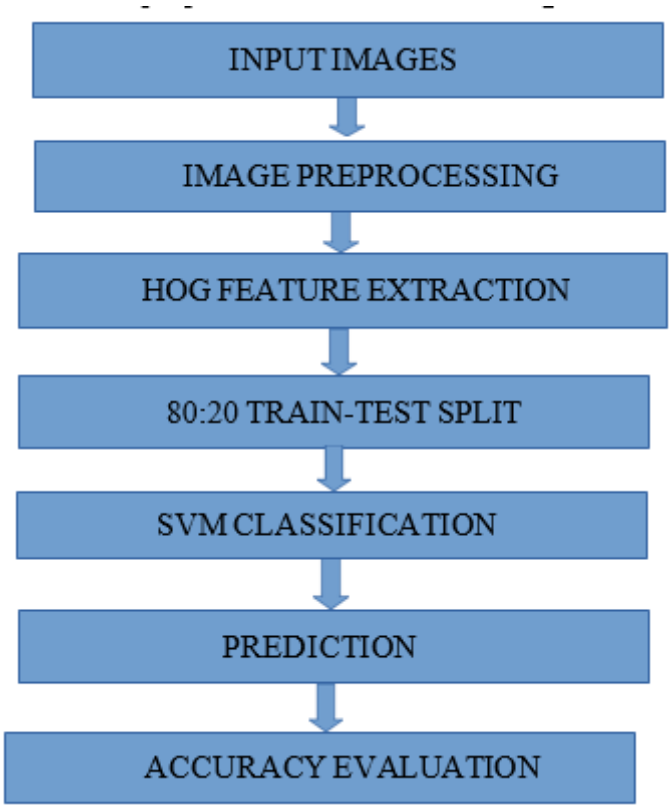


Figure 1. System flow of the proposed HOG-SVM face recognition method.

IV. HOG AND SVM METHOD

Histogram of Oriented Gradients (HOG) is used to extract facial features by analyzing the direction and magnitude of image gradients. The input facial image is converted into a suitable format, and gradient information is calculated to represent facial edges and structural patterns. The image is divided into small cells, and gradient orientations are summarized using histograms. These histograms are normalized and combined to form a feature descriptor.

The extracted HOG features are provided to a Support Vector Machine (SVM) classifier. The SVM uses a Radial Basis Function (RBF) kernel to classify the input image into one of the 17 subject classes. The model is trained on the training dataset and evaluated using unseen test images. This process is repeated separately for thermal, visible, and fused facial images.

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HOG-SVM algorithm steps:

1. Load thermal, visible, and fused facial images.
2. Preprocess the images.
3. Extract HOG features from each image.
4. Divide the dataset into training and testing sets.
5. Train the SVM classifier using the RBF kernel.
6. Predict subject classes for the test images.
7. Calculate and compare classification accuracy for all three modalities.

V. SYSTEM FLOW

The system flow of the proposed HOG-SVM face recognition method is shown below.

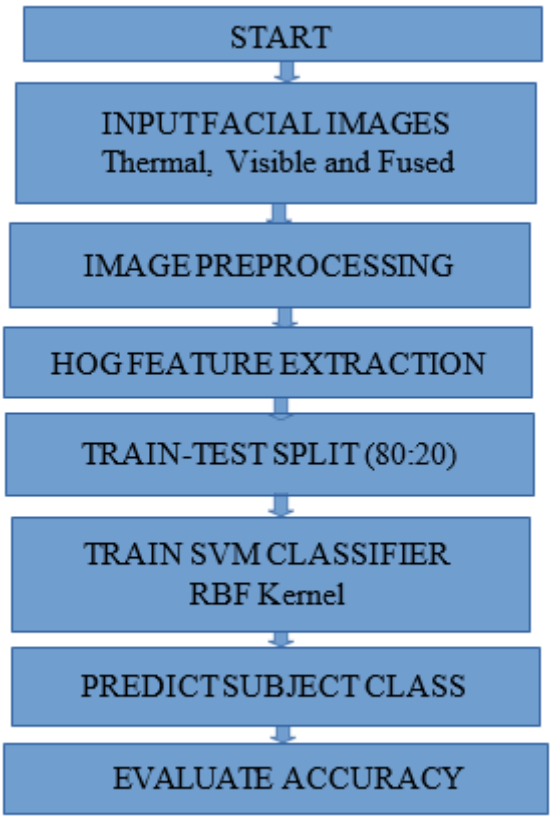


Figure 2. System flow of the proposed HOG-SVM face recognition method

VI. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed approaches were evaluated separately on thermal, visible, and fused facial images. Accuracy, precision, recall, F1-score, and confusion matrices were considered for performance analysis.

6.1 Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

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6.2 Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

6.3 Recall:

$$\text{Recall} = \frac{TP}{TP + FN}$$

6.4 F1-score:

$$F1_Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Where:

- **TP** = True Positive
- **TN** = True Negative
- **FP** = False Positive
- **FN** = False Negative

6.5 HOG-SVM Results

The HOG-SVM method was evaluated using thermal, visible, and fused facial image datasets containing 1,108 images from 17 subject classes. The classification accuracy was used to compare the performance of the three modalities.

Table I. Accuracy of HOG-SVM

Image modality	Accuracy (%)
Thermal	46.88
Visible	81.08
Fused	88.75

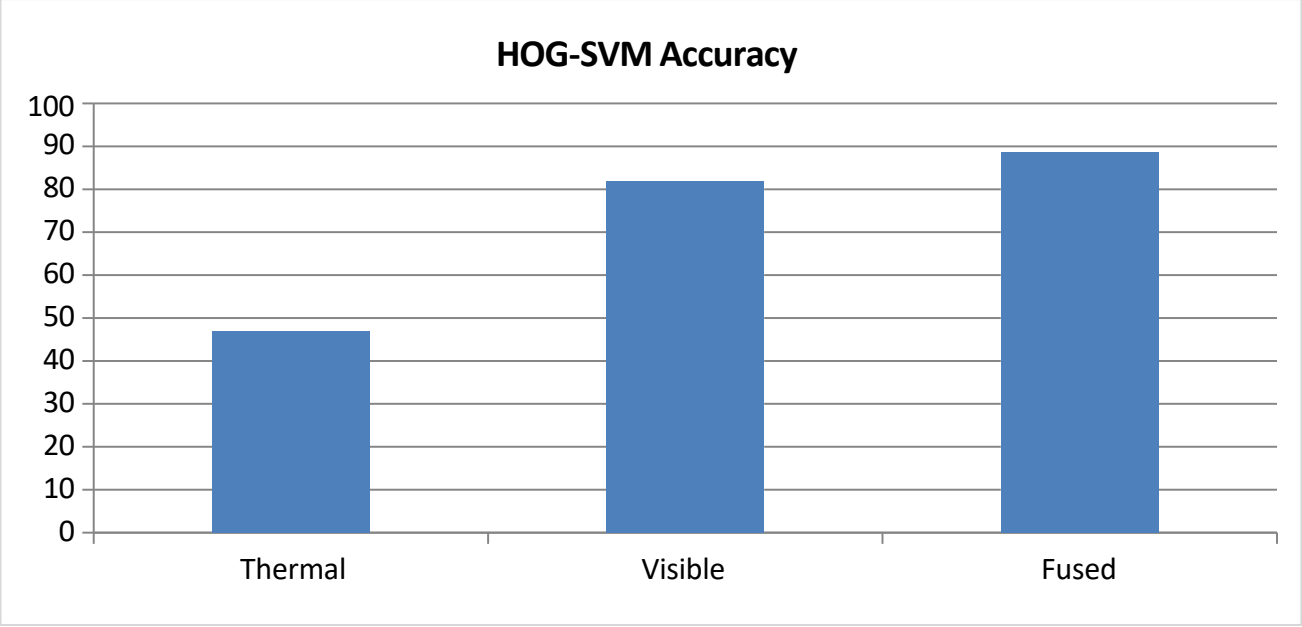


Fig.3. Comparison of HOG-SVM

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The experimental results show that fused images achieved the highest accuracy of 88.75%, followed by visible images at 81.08%. Thermal images achieved the lowest accuracy of 46.88%. Fused images performed 7.67 percentage points better than visible images and 41.87 percentage points better than thermal images.These results indicate that the HOG-SVM method performed best on the fused dataset under the evaluated experimental conditions. The lower accuracy for thermal images suggests that HOG features alone may not capture sufficient discriminative information for all thermal facial images. Further experiments using larger datasets and repeated train-test splits are needed to assess the consistency of these results.

VII. COMPARATIVE ANALYSIS

The performance of the HOG-SVM method was compared across thermal, visible, and fused facial image datasets. As shown in Table II, fused images achieved the highest recognition accuracy of 88.75%, followed by visible images at 81.08%. Thermal images achieved 46.88% accuracy.The fused dataset outperformed the visible dataset by 7.67 percentage points and the thermal dataset by 41.87 percentage points. These findings suggest that fused images provide more useful facial information for HOG-SVM classification in the evaluated dataset. However, the results are specific to the dataset and experimental settings used in this study.

Table II. Comparative accuracy of HOG-SVM

Image modality	Accuracy (%)	Rank
Thermal	46.88	3
Visible	81.08	2
Fused	88.75	1

VIII. CONFUSION MATRIX ANALYSIS

A confusion matrix is used to evaluate the classification performance of the HOG-SVM model by comparing actual subject classes with predicted subject classes. In this study, the model classifies facial images into 17 subject classes (S01–S17). Correct predictions appear along the main diagonal, while incorrect predictions appear outside the diagonal.Separate confusion matrices are generated for thermal, visible, and fused images to examine classification errors for each modality. The recorded accuracy results indicate that fused images achieve the highest overall accuracy (88.75%), followed by visible images (81.08%) and thermal images (46.88%). This suggests that the classification performance varies across the three modalities.The confusion matrices can help identify which subject classes are frequently misclassified. However, exact class-wise conclusions require the actual confusion matrix values. Therefore, the matrices generated by the implemented HOG-SVM model should be included to support a detailed analysis.

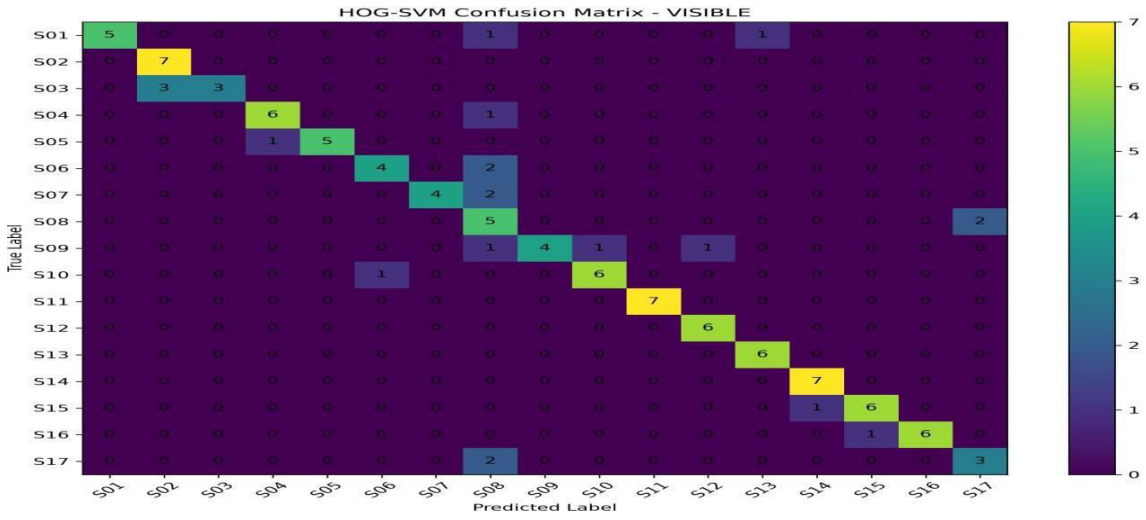


Fig.4. HOG And SVM Confusion Matrix -VISIBLE

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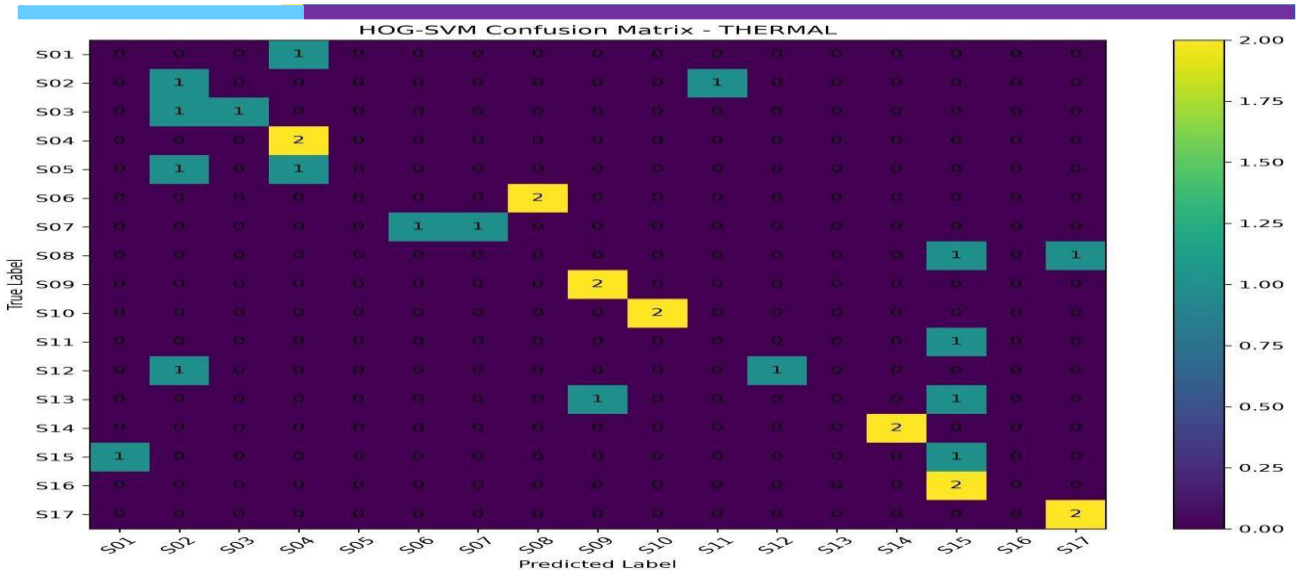


Fig.5. HOG And SVM Confusion Matrix –THERMAL

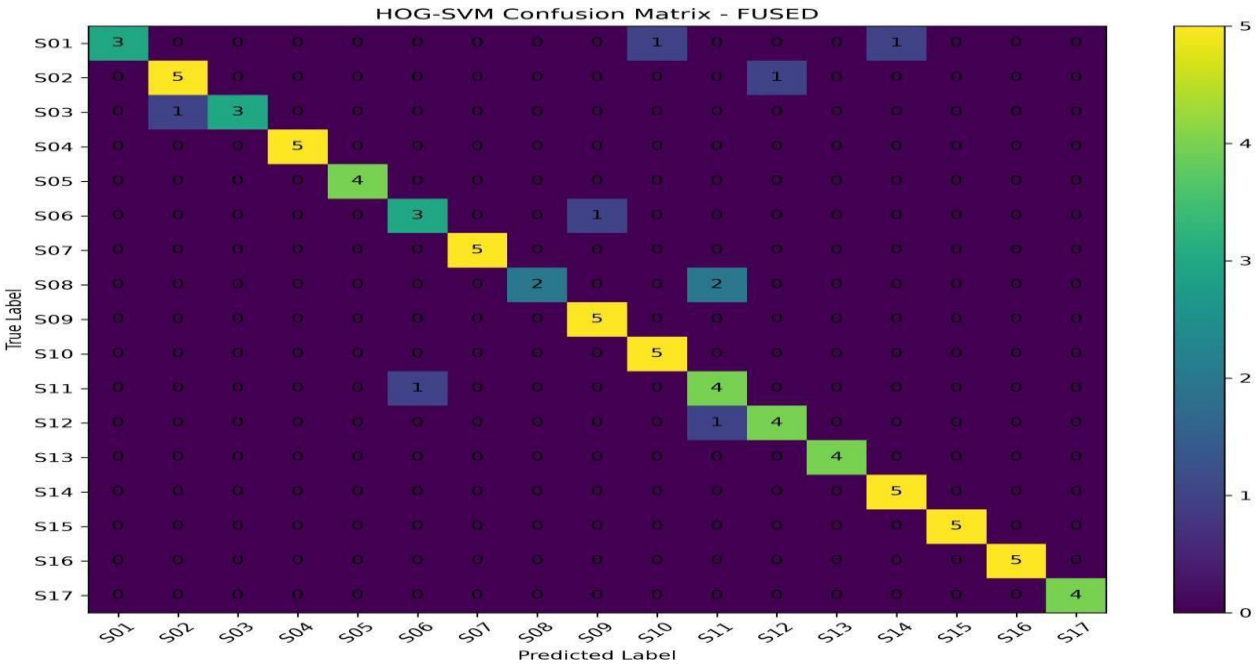


Fig.6. HOG And SVM Confusion Matrix –FUSED

IX. DISCUSSION

The experimental results demonstrate that the performance of the HOG-SVM face recognition method varies across thermal, visible, and fused images. Fused images achieved the highest accuracy of 88.75%, followed by visible images at 81.08%, while thermal images achieved 46.88%.

The better performance of fused images may be associated with the availability of complementary facial information from different imaging modalities. Visible images also provided better classification performance than thermal images in the evaluated dataset. The lower thermal accuracy suggests that HOG-based features may not adequately distinguish all subjects using the available thermal images.Overall, the results indicate that image modality influences HOG-SVM

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classification performance. However, these findings are limited to the dataset and experimental settings used in this study. Further evaluation using larger datasets, repeated experiments, and additional feature extraction methods could help establish the reliability of the observed performance differences.

X. LIMITATIONS

The proposed HOG-SVM method has some limitations. The dataset contains 1,108 images from 17 subject classes, which may not cover all real-world conditions. The thermal images achieve only 46.88% accuracy, indicating difficulty in distinguishing subjects using HOG features. Since HOG mainly captures edge and gradient information, it may not represent all complex facial characteristics. The results may also vary depending on image quality, illumination, preprocessing, and the train-test split. Therefore, further testing using larger and independent datasets is required to evaluate the method's reliability and generalization under different conditions.

XI. CONCLUSION

This study evaluated HOG-SVM for face recognition using thermal, visible, and fused facial images. The experimental results achieved accuracies of 46.88%, 81.08%, and 88.75%, respectively. Fused images produced the highest recognition accuracy, followed by visible and thermal images. These findings indicate that image modality affects the performance of the HOG-SVM method and that fused images performed best in the evaluated dataset. However, the lower accuracy on thermal images highlights the limitations of HOG-based feature extraction for this modality. Future work will focus on evaluating additional feature extraction techniques, improving thermal image recognition, and testing the method on larger and independent datasets.

REFERENCES

[1] M. M. Ambekar, S. N. Kakarwal, and S. S. Khedgikar, "Design, acquisition and collection of multimodal databases to increase accuracy and level of security," in *Proc. IEEE Virtual International Conference ICSIDEMP*, Aurangabad, India, 2020.
[2] S. N. Kakarwal and R. R. Deshmukh, "Face recognition using supervised learning," in *Proc. World Congress on Computer Science and Information Engineering*, Las Vegas, USA, 2012.
[3] S. N. Kakarwal and P. M. Paithane, "Automatic pancreas segmentation using RESNET-18 deep learning approach," *International Journal of System Research and Technologies*, vol. 2, pp. 104–116, 2022.
[4] S. N. Kakarwal and A. S. Gawali, "Context aware human activity prediction in videos using hand-centric features and dynamic programming-based prediction algorithm," *Journal of Integrated Science and Technology*, vol. 10, no. 1, pp. 11–17, 2022.
[5] A. Gawali and S. N. Kakarwal, "Enhancing early action prediction in videos through temporal composition of sub-actions," *Multimedia Tools and Applications*, vol. 84, no. 8, pp. 4253–4281, 2025.
[6] S. N. Kakarwal and R. Mapari, "Enhanced detection and segmentation of brain tumors using a Dense BW-CNN approach," *Wiley Journal of Engineering*, pp. 1–14, 2024.
[7] S. N. Kakarwal and R. R. Deshmukh, "Analysis of retina recognition by correlation and covariance matrix," in *Proc. 3rd International Conference on Emerging Trends in Engineering and Technology*, Goa, India, 2010, pp. 496–499.
[8] S. N. Kakarwal, K. P. Choudhari, and R. B. Patil, "Face recognition based on supervised learning," in *Proc. IEEE Virtual International Conference ICSIDEMP*, Aurangabad, India, 2020.
[9] S. N. Kakarwal and S. R. Choudhari, "Analysis of musical string instruments using k-NN," in *Proc. IEEE Virtual International Conference ICSIDEMP*, Aurangabad, India, 2020.
[10] S. N. Kakarwal, C. M. Gaikwad, and A. N. Ghule, "Classification based on soil attributes using non-imagery spectroscopic data," in *Proc. ICKE 2023*, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar, India, 2023.
[11] K. Gadekar, S. N. Kakarwal, and V. Mali, "Thermal face recognition using principal component analysis," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 13, no. 11, Nov. 2025, doi: 10.15680/IJIRCCE.2025.1311080.
[12] V. K. Mali, S. N. Kakarwal, and K. D. Gadekar, "Study of a simplified convolutional neural network for thermal face recognition tasks," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 13, no. 11, Nov. 2025, doi: 10.15680/IJIRCCE.2025.1311085.
[13] R. S. Ghiass, O. Arandjelović, A. Bendada, and X. Maldague, "Infrared face recognition: A comprehensive

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

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review of methodologies and databases," *Pattern Recognition*, vol. 47, no. 9, pp. 2807–2824, 2014, doi: 10.1016/j.patcog.2014.03.015.

[14] D. A. Socolinsky, A. Selinger, and J. D. Neuheisel, "Face recognition with visible and thermal infrared imagery," *Computer Vision and Image Understanding*, vol. 91, nos. 1–2, pp. 72–114, 2003, doi: 10.1016/S1077-3142(03)00075-4.

[15] G. Bebis, A. Gyaourova, S. Singh, and I. Pavlidis, "Face recognition by fusing thermal infrared and visible imagery," *Image and Vision Computing*, vol. 24, no. 7, pp. 727–742, 2006, doi: 10.1016/j.imavis.2006.01.017.

[16] S. G. Kong, J. Heo, F. Boughorbel, Y. Zheng, B. R. Abidi, A. Koschan, M. Yi, and M. A. Abidi, "Multiscale fusion of visible and thermal IR images for illumination-invariant face recognition," *International Journal of Computer Vision*, vol. 71, no. 2, pp. 215–233, 2007, doi: 10.1007/s11263-006-6655-0.

[17] G. Hermosilla, F. Gallardo, G. Farias, and C. San Martín, "Fusion of visible and thermal descriptors using genetic algorithms for face recognition systems," *Sensors*, vol. 15, no. 8, pp. 17944–17962, 2015, doi: 10.3390/s150817944.

[18] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, vol. 1, 2005, pp. 886–893, doi: 10.1109/CVPR.2005.177.

[19] O. Déniz, G. Bueno, J. Salido, and F. De la Torre, "Face recognition using histograms of oriented gradients," *Pattern Recognition Letters*, vol. 32, no. 12, pp. 1598–1603, 2011, doi: 10.1016/j.patrec.2011.01.004.

[20] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, pp. 273–297, 1995, doi: 10.1007/BF00994018.

[21] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[22] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the gap to human-level performance in face verification," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014, pp. 1701–1708, doi: 10.1109/CVPR.2014.220.

[23] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015,
pp. 815–823, doi: 10.1109/CVPR.2015.7298682.

[24] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002, doi: 10.1109/TPAMI.2002.1017623.

[25] I. T. Jolliffe, *Principal Component Analysis*, 2nd ed. New York, NY, USA: Springer, 2002, doi: 10.1007/b98835.



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