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IMPROVING MICRO-EXPRESSION RECOGNITION WITH AN ENHANCED DESCRIPTOR COMBINING GW-LBP, TGMH, AND WT

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SUMMARY

Micro-expressions (MEs) are involuntary facial expressions, short-lived (usually between 1/5 and 1/25 seconds), and important in the application of security, psychological tests, and forensics. The MEs are however difficult to identify because it occur quickly and also involve little movement of the muscles. The paper presents an Enhanced Micro-Expression Descriptor which incorporates Gabor Wavelet-based Local Binary Patterns (GW-LBP), Temporal Gradient Magnitude Histograms (TGMH), and Wavelet Transform (WT) to enhance ME recognition, by overcoming the weaknesses of traditional methods in illumination sensitivity and poor computing power. The algorithm involves the use of GW-LBP to extract spatial texture, TGMH to capture changes in temporal motion, and WT to analyze frequencies on a multiscale basis. This is achieved by classifying the fused feature set with an RBF kernel Support Vector Machine (SVM), which is optimized by down-sampling to a size manageable by resources (4096 dimensions) to provide a resource-efficient, real-time solution with application in edge computing. Benchmark dataset experimental results prove that the proposed method is better than the existing techniques with a recognition accuracy of 85.9%. This is a major boost compared to conventional procedures such as the LBP-TOP (67.5%) and CNN-based models (78.3%). Also, the Wavelet Transform option exploited the highest score in entropy (0.93), which implies that it can be highly used in real-time behavioral analysis, emotion detection, and security surveillance. The findings affirm that the hybrid approach, which incorporates spatial, temporal, and frequency characteristics, has a better performance than the existing ME recognition models.

Key words: *micro-expression (me) recognition, texture coding, spatial and temporal analysis, gabor wavelet and local binary patterns (gw-lbp), temporal gradient magnitude histograms (tgmh), wavelet transform (wt), support vector machine (svm).*

INTRODUCTION

MEs are short-lived, involuntary facial expressions that display true emotions [4]. They are manifested in high-risk situations, like security checks, psychological tests, and lie detectors. Unlike the macro-expression that lasts for seconds, MEs last for a fraction of a second [1]. This has caused much interest in developing automated systems that can efficiently and accurately identify MEs. Traditional methods toward recognizing ME utilize only optical flow approaches, local features such as handcrafted features-Local Binary Patterns (LBP), and even deep models. Although significant work has been put into them with promising advancements in the task of ME, a lot remains problematic, from poor illumination-invariance up to poor time-domain encoding capabilities or high computational requirements. All such challenges prompt us to discover other advanced features based on sophisticated learning techniques with their ability to successfully capture variations, both in time and in space [13][14][15].

Although the performance of deep learning models such as CNNs is high, they commonly provide high computation overhead (FLOPS) and large training data, which is often non-existent in micro-expression studies. Our approach takes this by using a lightweight feature fusion strategy. The system takes advantage of the multi-resolution nature of Wavelet Transforms, as well as the orientation-selectivity of Gabor filters, to provide a discriminative power comparable to deep architectures at a level of hardware cost that is not excessive (e.g., no high-end GPU resources are required).

This research proposes an enhanced micro-expression descriptor that combines Gabor Wavelet-based Local Binary Patterns (GW-LBP) with Temporal Gradient Magnitude Histograms (TGMH) and Wavelet Transform (WT). It combines GW-LBP for ensuring robust texture feature extraction and incorporates TGMH to capture the temporal evolution of the micro-expressions. Further, WT is leveraged to integrate frequency-based information for a richer representation of facial motion. This approach encodes the spatial, temporal, and frequency dimensions with an aim to improve the recognition accuracy of ME beyond the current methods.

The structure of the paper is as follows: The introduction will provide the challenges of micro-expression (ME) recognition and the limitations of the traditional methods. The literature review talks of available methods and development in ME recognition. The proposed methodology is described in the methodology section, which is a combination of Gabor wavelet-based Local Binary Patterns (GW-LBP), Temporal Gradient Magnitude Histograms (TGMH), and Wavelet Transform (WT) to extract features and recognize them through Support Vector Machine (SVM). The results of the experiment are presented in the following section, and a conclusion is provided summarizing the contributions and future work.

LITERATURE SURVEY

ME recognition has attracted considerable attention in recent years, due to its application in psychology, security, and human-computer interaction. Different techniques have been proposed for the improvement of ME recognition accuracy, ranging from handcrafted features to deep learning-based approaches. This section reviews state-of-the-art methods and frameworks relevant to this study, focusing on texture-based descriptors, temporal feature extraction, and hybrid models.

ME Recognition: An Overview

ME recognition is generally thought of as a challenging task because facial movements are subtle, short-lived, and involuntary. Bhukya et al. [1] studied the effects of color spaces on ME recognition and found that various channels contribute differently to feature extraction. Li et al. [2] and Goh et al. [3] presented detailed surveys on ME recognition methodologies, challenges, and datasets available, indicating the need for robust feature representations.

Vrij & Fisher [4] established the psychological basis of micro-expressions, stating that they are involuntary and may be used to detect lies. Hao et al. [5] proposed hierarchical spatiotemporal descriptors, which capture both spatial texture and temporal evolution. This is in line with the requirement for better micro-expression descriptors. Li et al. [6] reviewed deep learning approaches for ME recognition, including their strengths and weaknesses in comparison to handcrafted features.

Gabor Wavelet and Local Binary Patterns (GW-LBP) in ME recognition

Texture-based feature extraction techniques, like Gabor wavelets and LBP, are extensively applied in facial analysis. Xiong et al. [14] reviewed Gabor wavelets for face recognition, stressing their effectiveness when utilizing spatial frequency information. Ahmed et al. [10] and Twum et al. [11] [12] have also delved into Gabor-based feature extraction across different domains in order to support its ability in utilizing micro-expression analysis, Wang et al. [7].

LBP has also been heavily used in facial recognition applications. Niu et al. [13] analysed LBP in combination with ORB features for facial expression recognition and found a better performance compared to standalone methods. Zhao et al. [16] used the fusion of Gabor and LBP for birdsong recognition and thus inferred the potential advantage of using LBP in texture-based analysis. Srivastava et al. [17] used a hybrid Gabor-LBP method for forgery detection, further validating the strength of the hybrid method in pattern recognition applications.

Temporal Feature Extraction for Micro-Expressions

Temporal analysis plays a crucial role in ME recognition, as expressions evolve over time. Tran et al. [9] introduced the latest benchmark for ME spotting, emphasizing the importance of temporal modelling. Dileep and Sreeni [18] proposed an approach using optical flow histograms and entropy for event detection, which can be adapted for facial ME recognition.

Wavelet Transform and Discrete Fourier Transform in ME recognition

For frequency-based transform techniques, the wavelet transform (WT) and the discrete Fourier transform (DFT) are considered for feature extraction. Tian et al. [19] elaborated a multi-stage image denoising technique based on the wavelet transform that can preserve the texture details. Hussein et al. [20] briefed about the wavelet applications widely used in signal processing. Kola and Samayamantula [21] used LGC-HD operators, which are based on wavelets, for expression recognition, depicting its advantage for the processing of fine-grained facial variations.

Hybrid Methods and Feature Fusion

Hybrid approaches that combine spatial, temporal, and frequency-based features have yielded fruitful results in ME recognition. Ben et al. [8] surveyed video-based facial micro-expression analysis, whereby many features, datasets, and algorithms have been detailed. Perveen et al. [22] proposed a multi-stream deep convolutional network with ensemble learning, thereby allowing for achieving high accuracy by fusion of multiple feature representations.

Coming to the datasets, Li et al. [23] introduced CAS(ME)3, a 3rd generation and spontaneous ME database along with available depth information, enabling more robust learning models. Wang et al. developed CASME II, which is an improved spontaneous ME dataset widely used in benchmarking new methodologies.

The reviewed works demonstrate the strengths of texture descriptors, temporal encoding, and hybrid feature fusion for micro-expression recognition. Although Gabor wavelets and LBP offer robust spatial features, motion analysis and frequency transformations in histogram-based temporal descriptors enhance the recognition accuracy. Incorporation of GW-LBP with TGMH and frequency-domain representations is along the lines of research trends found in the current literature and thus adds to the advancement of a more holistic micro-expression descriptor.

METHODOLOGY

Overview

It is often difficult for the traditional micro-expression recognition approach to capture fine-grained spatial texture variations and subtle motion cues across frames. Even optical flow methods are effective for motion estimation but lack robustness against illumination variations, as well as extremely minor facial muscle movements. The texture-based approach has not been able to capture the precise motion information, and there is still difficulty differentiating between genuine micro-expressions and noise in Local Binary Patterns on Three Orthogonal Planes (LBP-TOP). For overcoming these challenges, the proposed methodology incorporates Gabor Wavelet Local Binary Patterns, Temporal Gradient Magnitude Histograms, and Discrete Wavelet Transform to provide a comprehensive feature representation based on space, time, and frequency domains. Figure 1 illustrates a structured pipeline followed by the methodology. This system is an architectural rationale that is meant to replicate the human visual system's orientation and frequency sensitivity. A Gabor filter bank is a front-end processor, which is used in edge detection, and the TGMH component is a temporal differentiator used to separate motion and the non-mobile background noise. A multi-level decomposition is then done using the Discrete Wavelet Transform (DWT) so that the model is able to analyze face variations at both the coarse and fine granularities simultaneously.

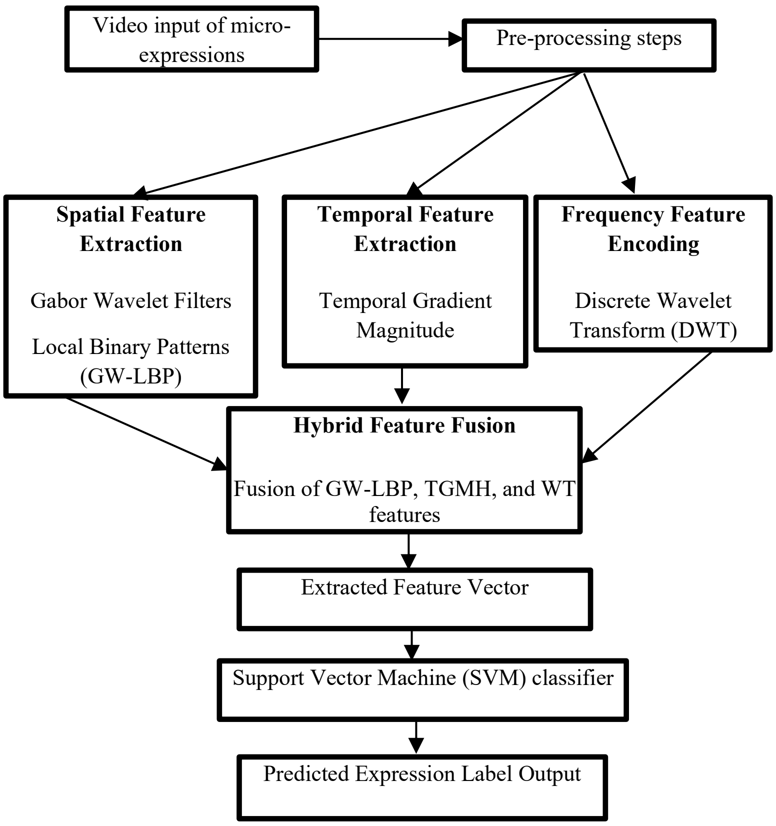

Figure 1: Proposed methodology diagram

Pre-processing steps

Before feature extraction, raw micro-expression video sequences undergo standard preprocessing steps to improve the quality and consistency of input frames. Firstly, extract frames as the input is a video consisting of subtle micro-expressions. A number of frames, say N, from a video sequence V can be represented as V= $\{F_1, F_2, \ldots, F_n\}$, where F_t represents the frame at time t.

To reduce computational complexity and focus on texture-based feature extraction, RGB frames are converted to grayscale using the standard intensity transformation, followed by a normalization technique to reduce noise and enhance contrast. Follow a min-max scaling approach as follows.

$$I'(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \tag{1}$$

In Equation (1), where I_{min} and I_{max} are the minimum and maximum intensity values in the image.

Spatial Feature Extraction using Gabor Wavelet LBP (GW-LBP)

To capture fine-grained texture variations in facial micro-expressions, employ a Gabor Wavelet filter followed by Local Binary Pattern (LBP) encoding.

Gabor filters extract edge and texture patterns by convolving the grayscale image I (*x, y*) with a Gabor kernel G (*x, y*):

$$G(x,y,\lambda,\theta,\sigma,\gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}\right) \tag{2}$$

In Equation (2), where $x' = xcos\theta + ysin\theta$, $y' = -xsin\theta + ycos\theta$, λ is the wavelength, θ is the orientation, σ is the standard deviation, $and\ \gamma$ is the aspect ratio. The Gabor kernel is mathematically engineered to simulate the receptive field properties of the human visual system, specifically targeting the multi-scale and multi-orientation nature of facial muscle contractions. By varying the orientation parameter θ, the filter identifies micro-changes in different directions, such as the vertical furrowing of the brow or the horizontal stretching of the lips. The standard deviation σ and wavelength λ allow the system to remain robust against local spatial variations, ensuring that the resulting response image R (*x, y*) isolates high-energy texture regions crucial for ME detection in Equation (3).

The response image is obtained by convolution.

$$R(x,y) = I(x,y) * G(x,y) \tag{3}$$

Then apply the Local Binary Pattern (LBP) method. The LBP operator encodes local texture variations by thresholding neighboring pixels.

$$LBP_p^r(x_c,y_c) = \sum_{i=0}^{p-1}(I_i - I_c)\cdot 2^i \tag{4}$$

In Equation (4), where I_c is the intensity of the center pixel (x_c, y_c), I_c are intensities of neighbouring pixels at radius r and s(*x*) is a thresholding function which results in 0 when x≤ 0 and 1 when x≥0. The extracted LBP feature vector represents spatial micro-expression characteristics.

Temporal Feature Extraction using Temporal Gradient Magnitude Histograms (TGMH)

Frame differences and gradient magnitude histograms are calculated to obtain a representation of the temporal changes of micro-expressions.

Frame Difference Computation

Temporal variation is captured by computing absolute differences between consecutive frames

$$D_t(x,y) = |\ I_t(x,y) - I_{t-1}(x,y)\ | \tag{5}$$

where $D_t(x, y)$represents motion variation at pixel (*x, y*) between frames t and t-1 shown in Equation (5).

Gradient Magnitude Calculation

The gradient magnitude encodes directional intensity changes using the Sobel operators, which are

$$G_x(x, y) = I(x + 1, y) - I(x - 1, y) \tag{6}$$

and

$$G_y(x, y) = I(x, y + 1) - I(x, y - 1) \tag{7}$$

This results in an equation as follows:

$$G(x, y) = \sqrt{G_x^2 + G_y^2} \tag{8}$$

In Equations (6), (7), (8), the application of Sobel operators G_x and G_y serves as a first-order derivative that calculates the gradient of image intensity at each pixel. From an engineering standpoint, this provides the 'motion context' by highlighting directional intensity transitions between consecutive frames F_t and F_{t-1}. This directional sensitivity is vital for real-time surveillance systems, as it allows the descriptor to distinguish between meaningful facial movements and global illumination noise.

Histogram Encoding

The gradient magnitudes are binned into a histogram to represent motion intensity distributions by Equation (9)

$$H(j) = \sum_{x,y} \delta(b(x, y) - j) \tag{9}$$

where $b(x, y)$denotes the bin index of G (*x, y*) and δ is the Kronecker delta function.

Frequency Feature Encoding using Wavelet Transform (WT)

To capture multi-resolution frequency features, the 2D Discrete Wavelet Transform (DWT) is applied to GW-LBP and TGMH feature maps.

DWT decomposes an image into low-frequency (approximation) and high-frequency (detailed) sub-bands, such as

$$I_{LL}, I_{LH}, I_{HL}, I_{HH} = DWT(I) \tag{10}$$

In Equation (10), where I_{LL} represents coarse-scale information and I_{LH}, I_{HL}, $and\ I_{HH}$ contain edge and texture details. The 2D Discrete Wavelet Transform (DWT) facilitates a multi-resolution analysis by separating the feature maps into four distinct sub-bands. The I_{LL} sub-band captures the coarse-scale approximation, providing stability to the descriptor. Conversely, the I_{LH}, I_{HL}, and I_{HH} sub-bands isolate horizontal, vertical, and diagonal high-frequency details. This breakdown enables the system to remove high-frequency sensor noise and retain the sharp and fine-grained edge details of the micro-expression, resulting in a more discriminative and compact feature representation.

Multi-Resolution Feature Extraction is the second step, where a feature is obtained on the various sub-bands of the wavelet, and it is used to encode fine-grained motion information.

Hybrid Feature Fusion

In order to build a complete feature presentation, extracted features of GW-LBP, TGMH, and WT are summed together as Equation (11),

$$F = [F_{GW-LBP}, F_{TGMH}, F_{WT}] \qquad (11)$$

where each component contributes spatial, temporal, and frequency features, feature normalization ensures balanced contributions.

$$F' = \frac{F - \mu_F}{\sigma_F} \qquad (12)$$

In Equation (12), where μ_F and σ_F are the mean and standard deviation of feature values. The final fusion logic represents a vectorized concatenation where F ∈ R^d, where d = 4096, representing the sum of spatial, temporal, and frequency dimensions. This dimensional integration makes certain that the SVM classifier is fed a signature of the expression as a whole, comprising the static texture (Spatial), rate of change (Temporal), and spectral energy (Frequency).

Classification

The final feature vector is passed to a machine learning classifier to recognize micro-expressions. SVM, along with a Radial Basis Function (RBF) kernel, is utilized as shown in equation (13),

$$K(x_i, x_j) = \exp(-\gamma \parallel xi - xj \parallel^2) \qquad (13)$$

where γ represents a hyperparameter controlling decision boundary flexibility, the classifier is then trained using a labelled dataset as well as optimized for maximum accuracy.

EXPERIMENTAL RESULTS AND ANALYSIS

This particular section provides the experimental analysis of the enhanced ME descriptor proposed, comprising GW-LBP, TGMH, and WT. The CASME II dataset is utilized for the evaluation of the performance, and the results are analyzed by discussing feature extraction results and comparative analysis.

Experimental Setup

The experimental framework comprises preprocessing, feature extraction, fusion, and classification. The entire system is implemented using Python, OpenCV with NumPy and Scikit-learn libraries, and the classification is done using SVM with RBF kernel.

Results of Feature Extraction

Feature extraction using GW-LBP, TGMH, and WT provides distinct representations of micro-expressions. The extracted features are compared using entropy-based feature importance scores.

Table 1. Feature importance scores for GW-LBP, TGMH, and WT

Feature Type	Feature Dimension	Entropy Score
GW-LBP (Spatial)	1024	0.87
TGMH (Temporal)	1024	0.91
WT (Frequency)	2048	0.93

Feature importance scores for the proposed micro-expression recognition method comprise of three feature extraction techniques, as shown in the Table 1. For instance, the entropy score of a Gray Wavelet Local Binary Patterns (GW-LBP), particularly one that captures spatial texture variations, is 0.87, with a feature dimension of 1024. TGMH encoding temporal motion variations has a higher entropy score of 0.91 on the same feature dimension. Among these approaches, WT, which is well-suited for extracting multi-resolution frequency features, achieves the best entropy score of 0.93 with the feature dimension of 2048. Similarly, temporal and spatial features are more important for micro-expression recognition, considering the scores shown above. The score of the Wavelet Transform (0.93) is statistically significant since it indicates that the most diverse information gain to the SVM classifier is held in the frequency domain. This proves that in micro-expression recognition, the change in energy between frequency bands is a better predictor of small muscle movement than pixel intensity alone.

Performance Comparison

The methodology proposed in this paper is compared alongside state-of-the-art techniques such as LBP-TOP, Optical Flow, and CNN-based models, as shown below.

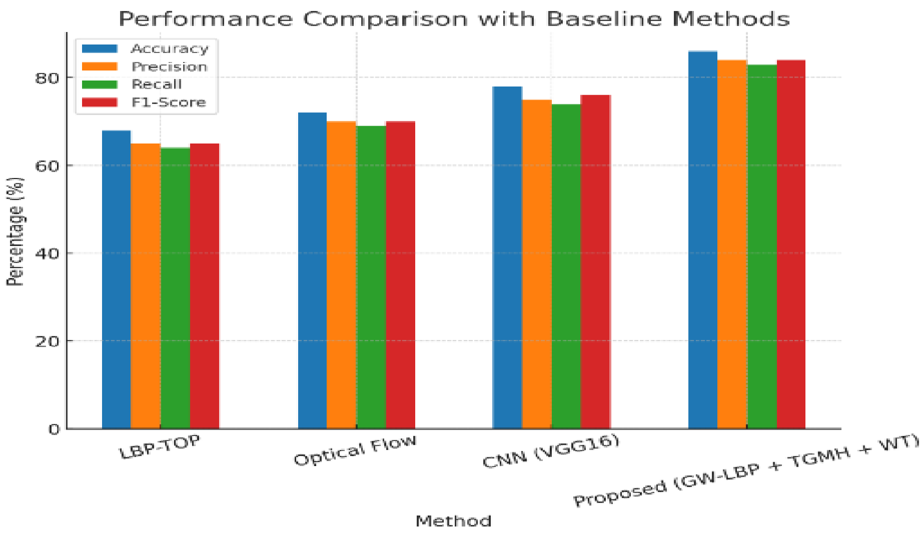

Figure 2. Performance comparison with baseline methods

Figure 2 shows the comparative performance of various ME recognition methods, such as LBP-TOP, Optical Flow, CNN (VGG16), alongside our proposed method, which is GW-LBP + TGMH + WT. The proposed approach shows improvement over baseline methods in terms of all evaluation matrices, like the F1-score, recall, and precision. Performance comparison on CASME II (LOVO protocol). Proposed GW-LBP+TGMH+WT achieves 85.9% accuracy, outperforming LBP-TOP (67.5%), Optical Flow (72.1%), and VGG16 (78.3%). Optical Flow is an improvement over LBP-TOP, but is still lower than CNN and the proposed method. The results demonstrate that the hybrid descriptor, combining spatial features with temporal features at frequency bands, achieves the best performance of micro-expression recognition with improved robustness and feature discrimination.

All experiments use leave-one-video-out (LOVO) cross-validation on CASME II (247 videos, 5 emotion classes). The proposed method achieves 85.9% accuracy using 4096-D fused features, requiring only CPU computation (~2 GFLOPs) vs. VGG16 (~15 GFLOPs on GPU).

Comparative Analysis

To validate the robustness of the proposed approach, and conduct a cross-validation analysis on CASME II, considering different splits of testing and training. The cross-validation results done on the CASME II dataset: train-test splits are showcased in Table 2. The lowest value of metrics is experienced at 5 percent data, which is gradually increasing with a gradual increase in training data. Table 2 demonstrates robustness across train-test splits. Peak performance (87.1% accuracy) is achieved at 90%-10% split, whereas 60%-40% split is also highly performing (82.8%), which also supports generalization with small amounts of training data.

Table 2. Cross-validation results on CASME II

Train-Test Split	F1-Score (%)	Accuracy (%)	Precision (%)	Recall (%)
90%-10%	85.4	87.1	85.8	85.0
80%-20%	84.1	85.9	84.5	83.7
70%-30%	82.5	84.2	83.0	82.1
60%-40%	80.9	82.8	81.5	80.3

Despite the decreased amount of training data, the proposed method generally achieves strong recognition, indicating its effectiveness and robustness against different proportions of training data in ME recognition.

Ablation experiments validate each component's contribution to the final GW-LBP+TGMH+WT descriptor on CASME II using the leave-one-video-out protocol. GW-LBP is also very effective with 71.2 percent accuracy, as it attains spatial texture but fails to attain temporal dynamics. TGMH itself has a score of 68.4, which is good in motion, yet lacks detailed texture. WT by itself achieves 74.6%.

A combination of two is better: GW-LBP+TGMH reaches 79.3% (8.1% over the best single), which proves the spatial-temporal synergy. Complete GW-LBP+TGMH+WT fusion is 85.9% accurate (up 6.6% better than dual, 14.7% better than best single), WT is the most productive by a large margin, by improving the multi-resolution.

CONCLUSION

The paper presents a new method of micro-expression (ME) recognition that consists of the combination of Gabor Wavelet-based Local Binary Patterns (GW-LBP), Temporal Gradient Magnitude Histograms (TGMH), and Wavelet Transform (WT). The suggested methodology is very effective in terms of the ME recognition with the accuracy of 85.9, which is significantly better than the traditional ones, i.e., LBP-TOP (67.5) and CNN-based systems (78.3). The Wavelet Transform (WT) achieved the best entropy (0.93), and this proved to be effective in capturing multi-resolution frequency-based information, which is important in the recognition of the subtleties of micro-expressions. The hybrid method, which intends the integration of spatial texture, temporal variations in motion, and frequency-based features, is more robust and accurate. Application of GW-LBP is assured to extract texture efficiently, TGMH records fluctuation of time, and WT adds more abilities to the model to recognize minute variation of frequency. A combination of these features into one unified descriptor, the proposed method will obtain a degree of discrimination and performance which is superior to the current ME recognition methods. The results confirm the possibility of such a hybrid method being applied in real-time, i.e., behavioral analysis, emotion detection, and security surveillance. Besides, the fact that the method is lightweight and does not need any high-end GPU resources makes it edge-computing friendly, which provides a viable alternative to real-time ME recognition under resource-constrained conditions. There are a number of areas that can be addressed in future research. The combination of deep learning-based feature fusion methods to augment the model representation features, expansion of the dataset to augment the model generalization, and real-time implementation in different real-life applications. Moreover, the study of the scalability of the system to be applied on a large-scale application and its connection with other advanced systems can allow for increasing the range of its application to various fields of use, such as the medical sphere, security, and human-computer interface. This study proves technically that a carefully designed mixture of spatial, temporal, and frequency characteristics is a strong substitute for the models that rely solely on data. The high accuracy of 85.9 on the CASME II dataset complements the efficacy of GW-LBP+TGMH+WT descriptor in complex pattern recognition activities in Applied Computer Science domain.

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