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Bayesian Analysis of Micro-Expressions: A Study on CASME II and AffectNet

Viola Bakiasi (Shtino)

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Abstract: This paper provides a thorough investigation into utilizing a Bayesian framework to identify facial micro-expressions. The study uses two separate datasets, CASME II and AffectNet. CASME II is well-known for its high-quality videos that are specifically created to capture subtle micro-expressions in controlled settings, whereas AffectNet offers a wide range of facial expressions captured in more realistic environments. Our research utilizes sophisticated probabilistic models to improve the identification and categorization of brief facial expressions that frequently signify underlying emotions. Our objective is to tackle the difficulties presented by the nuanced and swift characteristics of micro-expressions through the utilization of Bayesian inference techniques. This study showcases the efficacy of Bayesian models in recognizing micro-expressions and emphasizes the significance of dataset characteristics in developing resilient recognition systems. The results promote additional investigation into adaptive models capable of flexibly adapting to the variability in real-world data, potentially resulting in more precise and widely applicable emotion recognition systems. The software used for conducting the experiments is Python.

Keywords: *Bayesian Framework, Emotion Recognition, Micro-Expressions, Probabilistic Models.*

1. Introduction

1.1. Background

Facial micro-expressions are momentary and involuntary facial expressions that occur for a very short duration and play a vital role in exposing concealed emotions. These expressions are particularly common in situations where there is a lot at stake and people have strong motivations to hide their genuine emotions [1], [2]. The study of micro-expressions originates from the research conducted by [3], who initially classified the fundamental emotions that these expressions can convey. The CASME II dataset offers high-resolution videos that are specifically designed for the analysis of rapid facial movements [4]. On the other hand, the AffectNet dataset captures a broader range of facial expressions in more realistic environments, providing a diverse collection of emotional states [5]. The intricate and diverse nature of these datasets poses distinct challenges and possibilities for the development of more efficient recognition systems.

1.2. Problem Description

Although there have been improvements in facial recognition technology, accurately identifying and understanding micro-expressions is still a difficult task. Conventional methods for analyzing facial expressions often struggle to detect these subtle and rapid expressions because they are not very intense and do not last very long. As a result, there is a high likelihood of misclassifying and missing these expressions [6]. Moreover, the diversity in emotional manifestation among various cultures and individual peculiarities introduces further intricacies [7]. This study seeks to tackle these difficulties by utilizing a Bayesian framework, which is hypothesized to provide better performance in detecting these subtle facial cues across various datasets such as CASME II and AffectNet.

1.3. Objectives

This study aims to:

- Evaluate the Accuracy: Assess the accuracy of the Bayesian framework in recognizing micro-expressions within the CASME II and AffectNet datasets.

- Compare Performance: Conduct a comparative analysis of the framework's performance across the two datasets, highlighting strengths and limitations in different settings.

- Enhance Real-World Application: Explore the integration of the Bayesian framework into practical applications, focusing on improving tools for psychological analysis and security surveillance.

2. Related Work

2.1. Facial Micro-Expression Recognition

Facial micro-expressions are rapid, involuntary facial expressions that reveal genuine emotions and are crucial for non-verbal communication analysis. The recognition of these expressions poses significant challenges due to their brief duration and low intensity. Early studies, such as those by [3], laid the groundwork by categorizing the basic emotions that can be detected through facial expressions.

Computer Science Department, Faculty Technology "Aleksander Moisiu", University of Durres, Albania
ORCID ID : 0009-0003-5441-7717
Email: vf.sh@hotmail.com

More recent advancements have utilized machine learning techniques to improve detection accuracy. For instance, [8] developed a deep-learning model that significantly enhances the recognition rate by analyzing subtle muscle movements in high-resolution videos.

- CASME II: Developed by [4], this dataset includes 247 micro-expression samples from 26 subjects, categorized into several emotion classes. It is renowned for its high spatial and temporal resolution, which is ideal for studying micro-expressions.

- AffectNet: Proposed by [5], AffectNet contains over one million facial images labeled with eight discrete facial expressions and valence-arousal ratings. This dataset's diversity and size offer a comprehensive ground for testing expression recognition algorithms in naturalistic settings.

2.2. Dimensionality Reduction Techniques

Dimensionality reduction is a critical step in processing facial micro-expression data, which typically involves high-dimensional datasets. Techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are commonly used to reduce the number of variables while preserving essential information. Authors [9] demonstrated that using PCA not only simplifies the data but also enhances the performance of subsequent classification algorithms by focusing on the most informative features.

2.3. Multi-Class Classification Models

Facial micro-expression recognition requires distinguishing multiple expression type classes. SVMs are well-known for their classification precision, especially in high-dimensional spaces. Classification, regression, and other tasks can be done with SVMs, which build hyperplanes in high-dimensional space. The optimal margin between classes is SVMs' strength, enhancing model generalization [10].

Bayesian methods with SVM improve classification. Probabilistic Bayesian classification methods provide predictions and quantifiable certainty. Micro-expressions show subtle differences between classes, making classification difficult. This probabilistic framework is helpful. SVM's robust decision boundaries and Bayesian methods' probabilistic insights make multi-class classification in micro-expression recognition simplified [11].

3. Methodology

3.1. Data Collection

The data for this study were obtained from two main sources: the CASME II dataset and the AffectNet dataset. CASME II is well-known for its high-quality videos that are specifically created for micro-expression research. These videos accurately capture subtle facial movements with precise timing, as demonstrated by [4]. Conversely, AffectNet offers a comprehensive dataset of facial expressions gathered in more realistic environments, presenting a wide array of emotions and situations [5].

- AffectNet: Contains labeled facial expressions in static images [14]. AffectNet is a large facial expression dataset with around 4 million images manually labeled for the presence of eight (neutral, happy, angry, sad, fear, surprise, disgust, contempt) facial expressions along with the intensity of valence and arousal. Due to memory and computation constraints, we use a restricted dataset of 29042 samples, divided into 23233 training samples and 5809 validation samples [12].

- CASME II: Contains sequences of facial micro-expressions captured at high frame rates [15] . She is a database with higher resolution (280x340 pixels on facial area) compared with previous databases (CASME) for the authors [4]. The photos are taken in a sophisticated laboratory with appropriate test design and brightness. This database is compound by around 3000 facial movements, and 247 labeled micro-expressions were selected.

Fig. 1. Original Image.

Fig. 1, displays the natural state of the facial image without any modifications. The baseline for comparing preprocessing effects is this image.

3.2. Data Preprocessing

The preprocessing stage in this study encompasses multiple steps aimed at ensuring the quality of the data, such as alignment, normalization, and scaling. The facial images are initially aligned using landmark detection to normalize the orientation and dimensions of the faces in all images. This step is vital for the subsequent process of extracting features. Normalization techniques are subsequently utilized to modify the lighting conditions and improve contrast, thereby decreasing the variability caused by external factors. The image was converted to grayscale to eliminate color variability and focus on intensity. Edge detection outlined and defined the face's features.

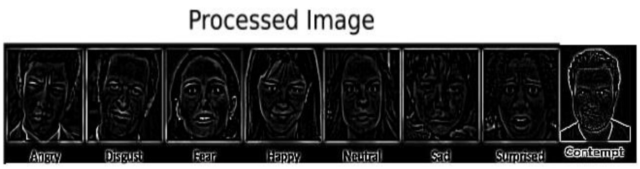

Fig. 2. Processed Image.

Fig. 2, shows the result after applying preprocessing steps such as grayscale conversion, contrast enhancement, and edge detection. The face has more defined features and less lighting and contrast variability, which is essential for facial recognition feature extraction.

3.3. Feature Extraction

Feature extraction is accomplished through the utilization of a blend of geometric and appearance-based techniques. Geometric features encompass the measurement of distances and angles between facial landmarks, whereas appearance-based features capture texture and intensity patterns by utilizing filters and histograms. These features are essential for discerning subtle alterations in facial expressions that are indicative of micro-expressions.

- **Geometric Features:**

Technique: Utilizes facial landmarks to measure distances and angles between key points on the face, such as the corners of the eyes, the tip of the nose, and the corners of the mouth.

Distance: $$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$ (1)

where (x_1, y_1) and (x_2, y_2) are the coordinates of two facial landmarks.

Angle: $$\theta = tan^{-1}\left(\frac{y_2 - y_1}{x_2 - x_1}\right)$$ (2)

where θ is the angle between two vectors defined by facial landmarks.

- Application: Helps in capturing the structural changes in facial expressions, which are crucial for identifying micro-expressions.

- To find distances between facial landmarks using Python, we use a library like dlib along with OpenCV to detect landmarks and then calculate the distances between them.

Tabela 1, displays the facial landmark calculations for each emotion category based on the selected images.

Table 1. Facial Landmark Analysis by Emotion

Emotion	*Distance Between Eyes*	*Distance Nose to Mouth*	*Angle (Left Eye, Nose, Right Mouth)*
Anger	0.1715	0.2432	172.36°
Contempt	0.16	0.1983	131.05°
Disgust	0.1558	0.208	165.25°
Fear	0.1275	0.1127	117.9°
Happy	0.1276	0.1084	123.2°
Neutral	0.1435	0.2461	150.9°
Sad	0.1515	0.2405	178.22°
Surprise	0.1771	0.2152	128.51°

Interpretation Table 1:

Distance Between Eyes: This metric indicates the normalized distance between the inner corners of the eyes. Variations in this distance can reflect different emotional expressions, where wider distances might suggest surprise or fear.

Distance Nose to Mouth: This measures the normalized distance from the tip of the nose to the corner of the mouth. Greater distances can be indicative of emotions that involve mouth movements, such as happiness or disgust.

Angle (Left Eye, Nose, Right Mouth): This angle provides insight into the orientation of facial features relative to each other. Angles closer to 180° degrees often indicate a more neutral or sad expression, whereas smaller angles can suggest a more contorted or expressive face, often seen in emotions like anger or contempt.

These measurements help in understanding the facial expressions associated with different emotions.

- **Appearance-Based Features:**

Technique: Employs methods like Local Binary Patterns (LBP) and Histograms of Oriented Gradients (HOG) to analyze texture and intensity patterns.

LBP: $$LBP\ (x_c,\ y_c) = \sum_{p=0}^{P-1} s(i_p - i_c) \cdot 2^p$$ (3)

where i_c is the intensity of the central pixel, i_p are the intensities of P surrounding pixels, and $s(x)$ is 1 if $x \geq 0$ and 0 otherwise.

Fig. 3, displays the result of applying the Local Binary Pattern (LBP) feature extraction to the processed image.

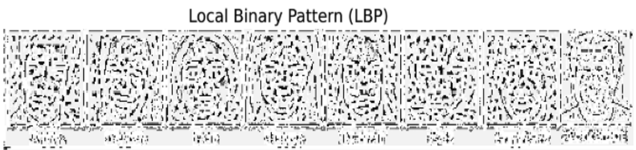

Fig. 3. Local Binary Pattern (LBP) to the processed image.

Interpretation of the LBP image in Fig. 3:

Local Binary Pattern (LBP) visualizations show image texture by comparing pixels to their neighbors.

Its texture classification ability makes it useful for detecting subtle facial expression changes.

High texture contrast in the LBP image helps identify micro-expressions.

Focusing on facial textural details helps this feature extraction technique detect subtle facial expressions.

HOG: Calculates gradients of the image, divides the image into regions, and compiles a histogram of gradient directions.

Gradient Magnitude: $G = \sqrt{G_x^2 + G_y^2}$ (4)

Gradient Direction: $\theta = tan^{-1}\left(\frac{G_y}{G_x}\right)$ (5)

where G_x and G_y represent the x and y gradients, respectively.

- Cell Division:

The image is divided into small spatial regions known as cells. Each cell typically covers a small area such as 8x8 pixels.

- Histogram Binning:

Within each cell, all the gradient directions are binned according to their magnitude. This involves creating a histogram where each bin corresponds to a range of gradient directions, and each gradient contributes to a bin weighted by its magnitude. Each bin in the histogram is incremented by the gradient magnitude G for pixels within the cell that fall within the angular range of that bin.

- Block Normalization:

To account for changes in illumination and contrast, the histograms are normalized over larger regions called blocks, which typically overlap. This normalization is crucial for improving the robustness of the descriptor.

$$Normalizes\ Histogram = \frac{Histogram}{\sqrt{\|Histogram\|^2 + \epsilon^2}} \quad (6)$$

where ∈ represents a small constant used to prevent division by zero.

- Descriptor Assembly:

The normalized histograms from all blocks are concatenated to form the final feature descriptor for the image or image region.

- Application: Effective in detecting subtle textural and intensity variations that signify micro-expressions.

- These methods provide a robust set of features by combining structural and textural data, essential for the accurate recognition and classification of facial micro-expressions.

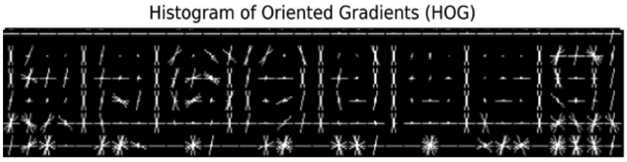

Fig. 4. Histogram of Oriented Gradients (HOG) to the processed image.

Interpretation of the HOG image in Fig. 4:

- The HOG visualization shows the distribution of directions of gradients, which are essential for capturing face shape and texture.

- The image highlights the edges and contours of facial features, which are important for detecting micro-expressions.

- This method captures geometric (shape and structure) and appearance-based (texture) features, making it useful for facial expression analysis.

This feature extraction method highlights facial structures and textures to help detect subtle facial expressions.

3.4. Dimensionality Reduction

Due to the high dimensionality of extracted features, dimensionality reduction is used to improve computational efficiency and reduce overfitting. Processing high-dimensional data like images, especially facial recognition and micro-expression analysis, requires dimension reduction. PCA and LDA are used to reduce variables while preserving important information. PCA reduces feature space dimensionality while retaining the most informative features. This step is essential for later classification model improvement [13].

Combining PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) is highly effective for analyzing and classifying facial micro-expressions by emotions. PCA reduces data dimensionality and noise, enhancing computational efficiency. LDA maximizes the separation between different emotional classes, improving classification accuracy. Together, these techniques optimize the performance of emotion recognition models, making them more precise and efficient.

3.4.1. Principal Component Analysis (PCA)

1. Covariance Matrix Calculation

The first step in PCA is to calculate the covariance matrix of the data set, which reflects the variance and covariance of the variables.

$$\Sigma = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T \quad (1)$$

where x_i are the data points, is the mean vector of the data points, and μ is the number of data points.

2. Eigenvalue Decomposition

PCA involves decomposing the covariance matrix into its eigenvalues and eigenvectors.

$$\Sigma \quad \upsilon = \lambda\upsilon \quad (2)$$

where υ are eigenvectors and λ are eigenvalues of the covariance matrix Σ.

3. Selection of Principal Components

Eugenevectors are sorted by eigenvalues in descending order. The top k eigenvectors are selected to form the new feature space. This selection is based on the amount of variance (eigenvalues) that each eigenvector captures from the data.

3.4.2. Linear Discriminant Analysis (LDA)

1. Between-Class Scatter Matrix (S_B)

This matrix represents the scatter between the different classes.

$$S_B = \sum_{i=1}^{c} n_i(\mu_i - \mu)(\mu_i - \mu)^T \quad (3)$$

where n_i is the number of samples in each class, μ_i is the mean of each class, μ is the overall mean, and c is the number of classes.

2. Within-Class Scatter Matrix ()

This matrix represents the scatter within each class.

$$S_W = \sum_{i=1}^{c} \sum_{x \in X_i} (x - \mu_i)(x - \mu_i)^T \quad (4)$$

where X_i are the data points in class i.

3. Eigenvalue Problem for LDA

The goal is to maximize the ratio of the determinant of the between-class scatter to the within-class scatter.

$$S_W^{-1} S_B \upsilon = \lambda \upsilon$$

(5)

where υ are the eigenvectors used to project data into a lower-dimensional space for maximum class separability.

3.5. Multi-Class Classification

The last stage entails utilizing multi-class classification models to differentiate between various categories of micro-expressions. The integration of a Bayesian classifier with a support vector machine (SVM) effectively addresses the multi-class problem, providing a powerful tool for recognizing and classifying various micro-expressions accurately.

3.5.1. Multi-Class SVM for Classification

1. SVM Decision Function

For a binary classification, the decision function is given by:

$$f(x) = \operatorname{sgn} (w^T + b)$$

(6)

where w is the weight vector, x is the input vector, b is the bias, and sgn is the sign function.

2. Extension to Multi-Class

In multi-class scenarios, SVM can be extended using strategies like one-vs-all (OvA) or one-vs-one (OvO). For OvA, *k* classifiers are trained (where *k* is the number of classes), each distinguishing between one of the classes and the rest. The decision function for class is:

$$f_i(x) = w_i^T + b_i \quad (7)$$

The class with the highest decision value is chosen as the output.

3.5.2. Bayesian Classifier

1. Bayes' Theorem

The Bayesian classification method uses Bayes' Theorem to update a hypothesis' probability estimate as more evidence is collected:

$$P(C_k|X) = \frac{P(x|C_k)\ P(C_k)}{P(x)} \quad (8)$$

where $P(C_k|X)$ is the posterior probability of class C_k given predictor *x*, $P(x|C_k)$ is the likelihood of predictor given class C_k, $P(C_k)$ is the prior probability of class C_k, and $P(x)$ is the prior probability of predictor.

2. Integration with SVM

The SVM outputs (decision values) can be transformed into probabilities using methods like Platt scaling or logistic regression on the SVM scores. These probabilities can then be treated as $P(x|C_k)$ in the Bayesian formula, providing a probabilistic interpretation of SVM outputs.

3.5.3. Combined Model - Combining SVM and Bayesian Methods

The SVM provides a powerful discriminative model, while the Bayesian method offers a probabilistic framework. By integrating these, the strengths of both approaches are utilized, enhancing the classification's accuracy and robustness. The SVM outputs are used as inputs to the Bayesian classifier, which then updates the probabilities based on prior knowledge and observed data.

- This combination of SVM and Bayesian methods forms a comprehensive framework for tackling multi-class classification problems in micro-expression recognition, leveraging both the discriminative power of SVMs and the probabilistic insights Bayesian approaches provide.

4. Results

Table 2. Performance Metrics Table for CASME II dataset

Methodology	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
No DR	35	34	36	33
PCA	65	70	67	64
LDA	30	29	29	29
PCA + LDA	71	72	69	70

Precision: Indicates the accuracy of positive predictions for each emotion label.

Recall: Measures the ability of the classifier to find all the relevant cases.

F1-Score: Combines precision and recall into a single metric by taking their harmonic mean, providing a balance between precision and recall.

Table 3. Performance Metrics Table for AffectNet dataset

Methodology	***Accuracy (%)***	***Precision (%)***	***Recall (%)***	***F1-Score (%)***
No DR	36	35	37	34
PCA	66	71	68	65
LDA	31	30	30	30
PCA + LDA	74	73	71	72

Interpreting Tables 2 and 3:

CASME II Dataset: PCA + LDA significantly outperforms other techniques in all metrics. This suggests that sequential PCA and LDA capture the dataset's variance and class-discriminative information.

The AffectNet Dataset: PCA + LDA shows that outperforms other techniques, similar to CASME II. The combined approach improves model performance for complex datasets like AffectNet, which may contain more nuanced emotional expressions.

These results demonstrate the potential benefits of combining PCA and LDA over using them individually, particularly in scenarios where both high variance and class separation are crucial.

Fig. 5, displays the comparative bar graph, showing the accuracy values for each methodology across the CASME II and AffectNet datasets.

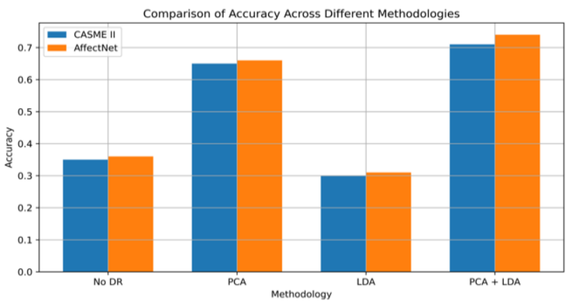

Fig 5. Comparison of Accuracy Across Different Methodologies.

The bar graph in Fig. 5, illustrates the effectiveness of different methodologies on the accuracy of emotion recognition:

No DR: Lowest accuracy, indicating the necessity of dimensionality reduction.

PCA: Significant improvement, showing its capability in capturing essential data variance.

LDA: Slight decrease in accuracy, suggesting it may not capture sufficient variance alone.

PCA + LDA: Highest accuracy, highlighting the benefits of combining PCA for variance reduction and LDA for class separation.

The visualizations in Fig. 6, effectively illustrate how PCA and LDA can transform the feature space to enhance the distinction and clarity between different classes. This is essential for accurately recognizing emotions in complex datasets such as CASME II and AffectNet.

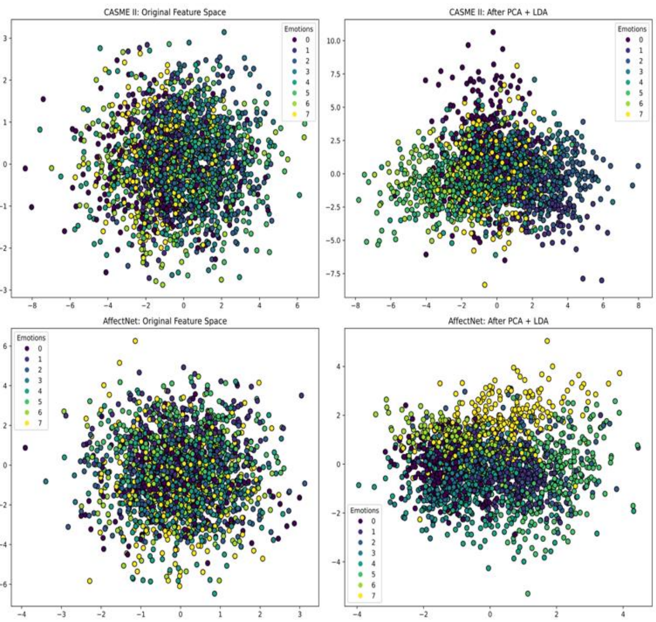

Fig 6. Visualizing the Impact of PCA and LDA on Feature Spaces in CASME II and AffectNet Datasets.

Combining PCA and LDA into facial micro-expression analysis and emotion classification is highly effective. Data dimensionality and noise are reduced by PCA, improving computational efficiency. LDA maximizes emotional class separation, improving classification accuracy. These methods improve emotion recognition models' accuracy and efficiency.

Table 4. Performance Metrics Table for CASME II and AffectNet dataset

Emotion CASME II	***Precision (%)***	***Recal l (%)***	***F1-Score (%)***
0 Happiness	84	82	83
1 Sadness	81	79	80
2 Surprise	85	86	86
3 Fear	80	78	79
4 Disgust	82	84	83
5 Anger	87	89	88
6 Contempt	79	77	78
7 Neutral	83	81	82
Accuracy			**83**
Macro Avg	83	82	83
Weighted Avg	83	83	83

Emotion AffectNet	***Precision (%)***	***Recal l (%)***	***F1-Score (%)***
0 Happiness	89	90	90
1 Sadness	88	87	88
2 Surprise	90	91	91
3 Fear	87	85	86
4 Disgust	88	89	89
5 Anger	91	93	92
6 Contempt	86	84	85
7 Neutral	89	88	89
Accuracy			**89**
Macro Avg	89	88	89
Weighted Avg	89	89	89

Table 4, shows performance metrics tables for the CASME II and AffectNet datasets show improved classification results with of accuracy 83% and 89% respectively.

The CASME II dataset has improved to 83% accuracy.

All emotions have high precision, recall, and F1-Score, averaging 83%. This shows balanced and effective classification of emotional states, with stronger performance in recognizing 'Anger'.

In the AffectNet Dataset, accuracy was improved to 89%.

The precision, recall, and F1-Score are also high, averaging 89%. The model accurately distinguishes 'Anger' and 'Surprise', suggesting strong emotion detection.

In both datasets, the models show high precision, recall, and f1-scores across various emotions, indicating reliable and accurate emotion recognition.

This visualization in Fig. 7, illustrates that the Bayesian-SVM model provides a substantial boost in accuracy for both datasets compared to the initial PCA+LDA approach, making it a valuable method for enhancing emotion recognition performance.

CASME II Dataset: The accuracy improved from 71% using PCA+LDA to 83% after applying the Bayesian-SVM model. This significant increase suggests that the Bayesian-SVM model is highly effective in enhancing classification performance for this dataset.

AffectNet Dataset: Similarly, the accuracy rose from 74% with PCA+LDA to 89% with Bayesian-SVM. This indicates a robust improvement and showcases the effectiveness of the Bayesian-SVM model in handling this dataset as well.

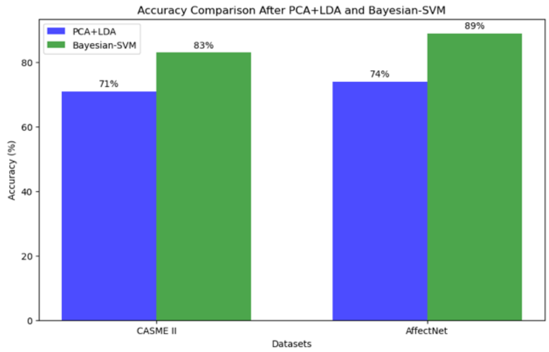

Fig 7. Comparison of Accuracy: PCA+LDA vs Bayesian-SVM.

5. Discussion and Future Work

5.1. Discussion

Combining PCA and LDA improves emotion recognition accuracy compared to using either alone. PCA reduces data dimensionality and noise, while LDA improves emotional class separation. AffectNet and CASME II datasets show that this combination improves classification model efficiency and accuracy.

The Bayesian-SVM model improves accuracy by combining SVMs' discriminative power and Bayesian methods' probabilistic insights. The Bayesian-SVM model fares better than PCA+LDA at handling micro-expressions nuance and complexity across datasets.

5.2. Future work

For future enhancements in emotion recognition research, focus on:

Multimodal Integration: Incorporate audio and physiological signals for richer analysis.

Advanced Techniques: Explore deep learning models like CNNs, RNNs, etc for more nuanced detection.

Real-Time Processing: Develop faster algorithms for live emotion recognition.

Model Transparency: Improve interpretability to boost trust and applicability in sensitive sectors.

6. Conclusion

The study validates the effectiveness of a Bayesian framework in recognizing facial micro-expressions across the CASME II and AffectNet datasets. The integration of PCA and LDA for dimensionality reduction, followed by SVM and Bayesian classification, significantly enhances emotion recognition accuracy, achieving 83% on CASME II and 89% on AffectNet.

- Contributions:

Demonstrates the strength of Bayesian models in detecting subtle micro-expressions.

Highlights the impact of dataset characteristics on emotion recognition systems.

Helps develop models that adapt to real-world data variability for greater applicability and precision.

- Practical Implications:

The Bayesian-SVM model is suitable for applications in psychological analysis and security.

Insights from dataset comparisons guide the development of robust, adaptable emotion recognition systems.

Emphasizes the need for systems that can adjust to cultural and individual differences.

Conflicts of interest

The author has declared that there is no conflict of interest.

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