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Enhancing Local Binary Pattern-Support Vector Machine (LBP-SVM) For Improved Facial Emotion Classification

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Abstract

Supervised Machine Learning algorithms like Support Vector Machines (SVMs), have emerged as powerful tools for classification, regression, and anomaly detection tasks. However, despite their high potential for emotion classification, SVMs face several challenges, including manual hyperparameter tuning, overfitting, difficulties in handling overlapping classes and noisy features, and failure to effectively detect action units. Addressing these challenges is important in improving the accuracy and robustness of facial emotion recognition systems. This study proposed improvements to the Local Binary Pattern - Support Vector Machine (LBP-SVM) framework to address these challenges. The Grid Search will be used to automatically select the optimal value for C and gamma parameters. To address the problem of overfitting and noisy features, Recursive Feature Elimination will be used to select the features that contribute the most to the class separability. Finally, to further enhance the accuracy of the model the researcher also combined the feature extracted from Facial Action Units to capture the dynamic characteristics of facial expressions. Experimental results on the CK+ dataset show the enhanced LBP-SVM achieves 98% accuracy, demonstrating improved robustness for recognizing subtle and complex emotional expressions.

Keywords: Support Vector Machines (SVMs), Facial Emotion Recognition, Local Binary Pattern (LBP), Hyperparameter Tuning, Recursive Feature Elimination

1. Introduction

1.1 Background of the Study

In today's era, the classification of facial emotions has become increasingly important due to its wide range of applications in various fields such as healthcare, education, security, public safety, and especially in human-computer interactions. Facial Emotion Recognition (FER) technology plays a crucial role in interpreting human emotions which is essential for effective communication and social interactions. (New Trends in Emotion Recognition Using Image Analysis by Neural Networks, a Systematic Review, 2023)

Supervised machine learning algorithms, such as Support Vector Machines (SVMs) have emerged as powerful tools for various machine learning tasks, including classification, regression, and anomaly detection. However, despite the promising capabilities of SVM in classification it still encounters multiple challenges that limit its effectiveness in emotion classification, including manual hyperparameter tuning, overfitting, difficulties in handling overlapping classes and noisy features, and failure to detect action

units. Thus, the enhancement of the model should be further studied to address these problems and improve its performance.
This study aims to further enhance the accuracy of SVM-based emotion recognition and exceed the accuracy achieved by previous studies. By addressing the challenges encountered in the model and implementing various techniques, this study aims to enhance the accuracy of SVM-based emotion recognition.

1.2 Statement of the Problem

Various factors influence the accuracy of SVM classification, and to enhance the existing algorithm the researchers will address the following:

1. **SVM requires manually tuning hyperparameters, particularly the gamma (γ) and C parameters, which can be time-consuming.**

Selecting the optimal value for c and gamma (γ) parameters is important in ensuring the model's performance. However manual hyperparameter tuning can be quite complex and time-consuming. (Nabat et al. 2022).

2. **Overlapping classes and the presence of noise make it challenging for SVMs to find a clear decision boundary that separates the classes accurately.**

Overlapping classes and noisy data make it difficult for Support Vector Machines (SVMs) to find a clear decision boundary, which can lead to misclassifications and overfitting. (Vuttipittayamongko et al. 2021). When data points and outliers are intermixed, the SVM might end up fitting the wrong patterns instead of accurately capturing the true class distributions. (Yang et al. 2023)

3. **As a local descriptor, LBP fails to capture the face's geometric structure. Subtle changes in facial landmark distances, like eyebrow contractions or mouth widening, are not effectively represented.**

LBP focuses on small, local patterns in an image but doesn't consider how facial features, like the eyes and mouth, are arranged in relation to each other. This means it can't capture the overall structure of the face or subtle changes, like an eyebrow-raising or a smile widening. As a result, it misses important details needed to fully understand expressions. (Patel & Kanani. 2021),

1.3 Objective of the Study

1.3.1 General Objective

The researchers proposed the modification of the Local Binary Pattern-Support Vector Machine (LBP-SVM) addressing the following problems: manual hyperparameter tuning, noise, and failure to detect action units. Enhancing the model's ability to classify emotion accurately.

1.3.2 Specific Objectives

The researchers aim to:

1. To address the challenge of manual hyperparameter tuning in SVM, the Grid Search algorithm will be implemented to systematically explore a given search space range of values for the gamma (γ) and C parameters.
2. Applying Feature Engineering techniques such as Recursive Feature Elimination to select features that contribute the most to class separability.
3. To address the failure of detecting action units, Mediapipe will be used to capture facial landmarks to measure the distances between features like the eyes, mouth, and eyebrows, enabling detailed analysis

of facial expressions for each emotion.

2. Review of Related Literature

This chapter covers the Related Literature Review (RRL), focusing on studies that explore the development of Facial Emotion Recognition systems and the algorithms that will be used in this research. By reviewing relevant literature, we aim to provide a comprehensive understanding of the existing methodologies and their effectiveness in enhancing emotion classification.

2.1 Facial Expression Recognition

The effectiveness of human communication relies not only on verbal communication but also on nonverbal cues, including gestures and facial emotions. (Ekman & Friesen. 1971), reported that there are a total of six emotions namely: anger, happiness, fear, surprise, disgust, and sadness that are readily recognized across different cultures. Technological advancement led to increased automation and enhanced accuracy in interpreting these nonverbal signals, particularly human facial emotion. One notable development is the advancement of Facial Expression Recognition (FER). It is a technology that analyzes facial expressions from both static images and videos to reveal information about one's emotional state (Vemou & Horvath, 2022).

The continuous advancement of technology has led to the enhancement of FER technology to further improve its ability to accurately capture and recognize human emotion through facial expressions. R.Guo & H.Guo et al. (2024), conducted a systematic literature review about the Development and application of emotion recognition technology. The review shows that the advancement of FER has benefited remote emotion recognition and treatment in hospital and home environments by healthcare professionals. It also caused a great shift from the traditional subjective way of emotion assessment to a multimodal emotion recognition that is based on objective psychological signals.

Various techniques like feature-based methods such as Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG), machine learning approaches like Support Vector Machines (SVM) and k-nearest Neighbors (k-NN), as well as deep learning methods including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been studied to improve the accuracy of FER. A study conducted by Mishra & Bhatt. (2021) reviews the different FER algorithms divided into two methods, the feature-based techniques and the model-based. The feature-based methods highlighted in the paper are the Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), and Gabor Filter Texture (GFT). Another study by Khan (2022) reviews conventional Machine Learning (ML) and some Deep Learning (DL) approaches in FER. The paper gives a holistic review of FER using the ML and DL methods, discussing and comparing its benchmark results. Algorithms such as SVM, K-NN, and Decision Tree are reviewed for the ML methods. Mellouk & Handouzi. (2020), conducted a review on the use of deep learning in facial emotion recognition. Reviewing the recent advancements in the field of FER using deep learning architectures. The study presents various studies conducted about FER. The paper showed that the most used architecture is the Convolution Neural Network (CNN), some combined with Long short-term memory (LSTM).

Sajjad et al. (2023) conducted a detailed survey on Deep Facial Expression Recognition (FER), exploring its various dimensions including the challenges it faces, its applications, and potential future directions. The survey highlights that FER has a broad range of applications, from its use in security, learning, and the prognosis and diagnosis of neurological disorders. The study also highlighted the challenges of FER that hinder its ability to effectively recognize emotions. Such as scarcity of FER datasets, illumination, face pose, occlusions, aging, and low resolution.

2.2 Support Vector Machine

Support Vector Machine is a supervised machine learning algorithm primarily used for classification and regression tasks focusing on maximizing margins between different classes. SVM is deeply rooted in the principles of statistics, optimization, and machine learning. It was officially introduced by Boser, Guyon, and Vapnik in the year 1992 during the fifth annual Association for Computing Machinery Workshop on Computational Learning Theory. Awad & Khanna (2015) stated in their study that the basic principle of SVM involves finding the hyperplane that separates data points into different classes and maximizing the margins between them. The goal of SVM is to ensure the optimal classification of unseen data by finding its maximum margin hyperplane.

SVM addressed different computational challenges and its functionality in various applications such as multiclass SVM, Fuzzy SVM, LS-SVM, Structured SVM, and many more. The latest proposed SVM-Type Algorithm is the "Least Squares Minimum Class Variance Support Vector Machines" by Panayides & Artemiou, (2024). this variant of SVM demonstrates an analytical solution and combines class variants with the least squares approach, resulting in a faster and more computationally efficient solution. The proposed algorithm addresses singular matrix inversion and improves computational time without losing accuracy.

Support Vector Machines have been applied in various fields such as face recognition, disease diagnostics, text recognition, sentiment analysis, plant disease identification, and intrusion detection systems for network security applications. (Abdullah & Abdulazeez, 2021). Thus, according to Guido et al., (2024), The application of Support Vector Machines in the healthcare domain has been used for a variety of tasks including diagnosis, prognosis, and prediction of disease outcomes. ML techniques specifically SVM's are utilized in healthcare services to enhance experts' decision-making in the clinical environment enhance patient outcomes and reduce errors.

It is developed in a framework of statistical learning theory. It became popular and has several applications, from time series prediction to facial recognition. It is used for classification and regression, but they are primarily used for classification. Its main goal is to find the hyperplane in an N-dimensional space that distinctly classifies the data points. Though the model's use has succeeded, it still suffers different challenges. Link

2.3 Local Binary Pattern

Local Binary Pattern (LBP) has become a key tool in computer vision and image analysis, providing a straightforward yet effective approach for texture classification and pattern recognition. It is a non-parametric descriptor and is used to extract, analyze, recognize, and classify the different modality images, and summarize the local patterns of image characteristics efficiently. (Singh & Gagandeep, 2022). The process of LBP consists of two main steps the thresholding and the encoding step. The first step (thresholding) extracts information about the local binary difference of 1 or 0. Then in the second step (encoding), the generated binary numbers from each pixel are converted into decimal values. Before applying the LBP algorithm, it is crucial to preprocess the image by converting it to grayscale. This is because LBP operates on intensity values and is designed to handle single-channel photos effectively.

Due to its versatility, LBP has been used in different applications. In text recognition, for instance, it helps by analyzing the unique textures of different characters, which makes it easier to identify and classify various text patterns. In a study by C. Sari & W. Sari et. al (2023), LBP is used to improve the accuracy of Multi Support Vector-Based Javanese Handwriting Character Recognition. Another study conducted by Nene & Jain et. al (2021), integrates Local Binary Pattern Histograms (LBPH) with Raspberry Pi for facial recognition. Using the Haar-cascade for face detection and Local Binary Pattern Histogram, they are able to create an efficient algorithm for face recognition. Beyond these, LBP is also making strides in medical imaging. It's used to identify and categorize patterns in medical scans, which can be invaluable for spotting abnormalities or classifying different types of tissue. Dheepak & Johnvictor et. al (2023), proposed the integration of both Gray-Level Co-Occurrence Matrix (GLCM) features and Local Binary Pattern (LBP) features to conduct a quantitative analysis of tumor images (Glioma, Meningioma, Pituitary Tumor). The result shows high accuracy in classifying all three classes of brain tumors, demonstrating a 100% true positive rate and 0% false negative rate indicating that there is a great balance between sensitivity and specificity. In all these areas, LBP's ability to capture and analyze texture makes it a powerful tool for understanding and interpreting visual information.

2.4 Hyperparameter Tuning

To ensure a machine learning algorithm is both accurate and effective, several factors come into play. One key aspect is optimizing hyperparameters. These parameters often substantially influence the complexity, behavior, speed as well as other aspects of the learner, and their values must be selected with care in order to achieve optimal performance (Bischl & Binder et al., 2022). The performance of machine learning algorithms is highly sensitive to hyperparameter settings. To achieve optimal results, users must carefully select an efficient tuningstrategies, define tunable hyperparameters, and specify their corresponding ranges, saclae, and potential prior to distribution for sampling (Probst et al., 2018). As manual hyperparameter tuning and the manual process of trial and error to find the optimal value are considered time-consuming, various hyperparameter optimization (HPO) methods are studied.

Hossain & Timmer et al. (2021), analyze some of the methods used in hyperparameter optimization such as Grid search, Random search, and Bayesian Optimization (BO). These methods are applied to machine learning like Random Forest, SVM, KNN, and ANN. Another study by Elgeldawi & Sayed et al. (2021), tested various hyperparameter tuning techniques such as Grid Search, Random Search, Bayesian Optimization, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA).

The machine learning models are then used for solving an Arabic sentiment classification problem. The result shows that Bayesian Optimization obtained the highest accuracy with 95.6208%.

A study "Face Recognition Method based on Support Vector Machine and Rain Optimization Algorithm (ROA)" by Nabat et al. (2022) highlighted the importance of setting the hyperparameter of SVM in optimizing the performance of the model in classification. Tuning the parameters correctly enables the algorithm to identify the local and global extremum. The c parameter controls the balance between error minimization and margin maximization. The researchers proposed the ROA-SVM model to find the optimal parameter to improve SVM performance in Face Recognition.

2.5 Feature Selection

Feature selection is a process in machine learning and statistics that involves identifying and selecting a subset of relevant features (variables, predictors) from a dataset for model construction. In the study of Spencer et al. (2020), The primary objectives of feature selection are to simplify models, reduce computational costs, and enhance model performance by eliminating irrelevant or redundant data. This process is crucial in handling high-dimensional data, where the presence of numerous features can lead to overfitting and decreased model generalization.

Bouchlaghem et al. (2022) stated that the methods of feature selection algorithms are cathegorized into supervised, semi-supervised, and unsupervised methods. Supervised feature selection is usually categorized into three approaches. First, the filter methods evaluate features based on intrinsic properties like correlation with the target variable. Wrapper methods assess feature subsets by training and testing a model but are computationally intensive and prone to overfitting. Lastly, embedded method performs feature selection during model training, offering a balance between efficiency and consideration of feature interactions. To assess the performance of feature selection, the authors used ReliefF, Mutual Information (MI), Support Vector Machine Recursive Feature Elimination (SVM-RFE), Sequential Forward Selection (SFS), Lasso, and Ridge. The result concluded that Practitioners should select feature selection methods based on their dataset's characteristics and available computational resources. For large datasets, fast filter methods like ReliefF or MI are ideal, while wrapper or embedded methods are better suited for tasks requiring feature interaction analysis, despite their higher computational costs.

In a study of Ali et al. (2024), Despite the notable advancements in feature selection methods, in the development of robust algorithms such as ReliefF and mRMR, and the integration with machine learning models for simultaneous feature selection and training, and their applicability to high-dimensional datasets, feature selection still faces challenges such as scalability issues as data complexity increases, difficulties in managing noisy and incomplete data, and the ongoing task of balancing relevance and redundancy to avoid overfitting. Addressing these issues is essential to further enhance the efficiency and robustness of feature selection techniques.

In the article “Cattle Identification Using LBP Descriptor And SVM Classifier” by Rajankar et al. (2019), when analyzing complex data the issue of curse dimensionality occurs as it refers to the fact that the number of variables included in the analysis can negatively affect the analysis. With many variables, a lot of memory and processing power is needed which causes the characterization algorithm to over-fit the training sample and poorly perform on a new sample. The researchers used a feature extraction technique to reduce the number of variables by creating a new set of variables that captures the important information from the original data.

The study “Selecting critical features for data classification based on machine learning methods” by Chen et al. (2020) explores the importance of feature selection in machine learning particularly in dealing with high-dimensional datasets. The authors emphasize that effective feature selection can simplify models, reduce training time, enhance generalization, and mitigate the curse of dimensionality. They used Random Forest (RF) methods, including varImp(), Boruta, and Recursive Feature Elimination (RFE), to identify significant features across three datasets: Bank Marketing, Car Evaluation, and Human Activity Recognition Using Smartphones. The study also compares the performance of various classification models like Random Forest, Support Vector Machines, K-Nearest Neighbors, and Linear Discriminant Analysis, both with and without feature selection. The findings indicate that RF-based feature selection methods improve classification accuracy and performance, with RF classifiers consistently outperforming others in the experiments.

In the article “On the Class Overlap Problem in Imbalanced Data Classification” by Vuttipittayamongko et al. (2021), class imbalance and class overlap negatively impact the performances of learning algorithms, especially in SVM. The low overlap degrees do not significantly affect the classification results, however, SVM performance was significantly degraded in overlapping regions as simulated data showed inconsistencies in imbalance degree and situation, leading to inconclusive results. While in the article "Image Classification with Deep Learning in the Presence of Noisy Labels" by Yang et al. (2023). The impact of noise on image classification performance especially the noise in image datasets and label noise complicates the learning process by introducing errors that mislead the model. The study highlights various techniques to mitigate this issue such as noise-robust algorithms and preprocessing methods to clean the data.

2.6 Facial Action Units

Recognizing facial emotions takes into consideration several factors, like the movement of facial muscles, the intensity of expression, and temporal dynamics. In the study "Classification of Facial Emotions Using Machine Learning" by Patel & Kanani (2021), the Action Unit (AU) is a key feature to be considered in order to accurately classify facial emotions. Action Units are the terms used by Facial Action Coding System (FACS) for individual facial muscle actions. These units are shown as changes in specific facial regions, like eyebrow raising, lip stretching, and eye closure, corresponding to various emotions, such as happiness, sadness, anger, and surprise. Combining machine learning models with the intensity of Action Units offers a means to obtain subtle variations in facial expressions, which enhance precision and robustness in emotion classification.

The study, "Recognition of Emotion Intensities Using Machine Learning Algorithms: A Comparative Study" by Mehta et al., (2019), examines the potential of automatically recognizing facial emotions and their intensities, which is important not only to behavioral biometric systems but also to human-machine interactions. The authors also discuss three feature extraction techniques: Gabor filters, Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LBP), with three classification algorithms: Support Vector Machine (SVM), Random Forest (RF), and k-nearest Neighbors (kNN). Their results indicate that combining LBP with SVM yields the highest recognition accuracy regarding emotions and their intensity, thus providing applications for real-time behavioral analysis and systems such as crime prediction and drowsy driver detection. The author highlighted the importance of using Action Units to improve the classification of emotion further. For measuring the intensity of emotions, it is not only required to improve the accuracy of feature extraction algorithms but also exploiting the facial actions.

2.7 LBP-SVM Existing Studies

In the article "Facial Expressions Recognition Based Using LBP and SVM Classifier" by Singh et al. (2019), The application of facial expression recognition is in human-computer interaction and data-driven animation. Thus, computers are having a problem in recognizing facial expressions due to the large variations. The researchers propose a system that uses Local Binary Patterns (LBP) to extract features from faces and a Support Vector Machine (SVM) to classify facial expressions. However, the study can only classify data in these factors: Normal, Cool, Surprised, Closed Mouth, and Smile reactions.

The article "A Review on Facial Expressions Recognition Based on LBP & SVM" by Patel and Tiwari (2020) improves the study of "Facial Expressions Recognition Based Using LBP and SVM Classifier" by Singh et al. (2019). The study by Patel and Tiwari (2020) discussed facial expressions and how computers can recognize them. The process involved in detecting faces in an image then pre-processing the facial area, and extracting features from the images. These features are then classified into categories of Expression: fear, happiness, sadness, and Action Units (AUs): eye open, mouth stretched. The results of this study are promising compared to the baseline study of (Patel and Tiwari, 2020) as the methods perform better than the other existing methods.

3. Methodology

This chapter discusses and presents the design and method used in the testing of the proposed enhancement of the SVM algorithm. The simulation is done for both existing and enhanced algorithms to compare their accuracy in emotion recognition.

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3.1 Requirement Analysis

For the training and evaluation of the model, the following parameters are considered:
c parameter - allows us to control the trade-off between the margin and misclassifications.
gamma - defines how far the influence of a single training example reaches, with low values meaning 'far' and high values meaning 'close'.
kernel function - is a method used to convert data into a higher-dimensional feature space where it may be linearly separated.

Table 1: Parameter Configurations for Proposed Algorithm

Parameter Configurations for Proposed Algorithm	
c parameter	[0.1, 1, 10, 100]
gamma parameter	[0.001, 0.01, 0.1, 1]
kernel function	RBF (Radial Basis Function)

The table above shows the configuration of the parameters for the proposed algorithm. For the c parameter and gamma, the provided range of values will be used for the hyperparameter tuning using the Grid Search optimization to find the best hyperparameter value. The kernel function used in the model is the RBF kernel.
For the datasets, the CK+ (Extended Cohn-Kanade) dataset will be used in the simulation. It is a popular and widely used dataset for Facial Emotion Recognition. The CK+ is obtained from Kaggle. It contains the sequence of different facial expressions capturing the progression of facial expressions from a neutral state to the peak of the expression.

3.2 Conceptual of the Enhanced LBP-SVM Algorithm

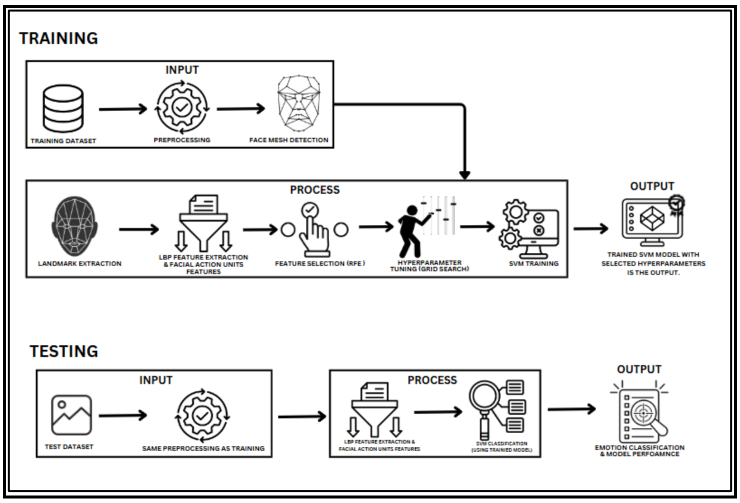

Figure 1: Conceptual Framework of the Proposed Algorithm

The figure above shows the enhancement of the LBP-SVM algorithm for improved emotion recognition. The process starts with the training of the proposed model by inputting the dataset from Kaggle and preprocessing these data including the face detection, cropping, resizing, and grayscale conversion of the images, After the preprocessing is the Facial Mesh Detection using Mediapipe. Then, the processed dataset will undergo the process shown in the figure. First is feature extraction using LBP, followed by capturing the Facial Action Units (AU) using the Mediapipe libraries in Python, and feature selection using RFE. After that, the Grid Search will be used to find the best hyperparameter tuning for the model and will be used in SVM training.

In the testing phase of the model, the researcher will implement the model in video input the same preprocessing as training will be done in the testing input. Then the process will include LBP extraction and the trained model will be used to classify and recognize the detected emotion. The output will consist of the evaluation of performance using the accuracy, precision, and f1-score to determine the performance of the trained model in its application in video inputs.

3.3 Testing

3.7.1 Accuracy - indicates the proportion of correct predictions made by a model

$$\text{Accuracy} = \frac{TP\text{ - }TN}{\text{Total Sample}}$$

Formula:

Where:

True Positives (TP): Correctly predicted positive cases.

True Negatives (TN): Correctly predicted negative cases.

Total Samples: The sum of all true positives, true negatives, false positives, and false negatives.

3.7.2 F1 Score - is a performance metric that combines Precision and Recall into a single value, offering a balance between the two.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Formula:

Where:

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

Precision:

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

Recall:

3.7.3 Precision - indicates the proportion of correctly predicted positive instances out of all instances predicted as positive.

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

Formula:

Where:

True Positives (TP): The number of correctly predicted positive instances.

False Positives (FP): The number of instances incorrectly predicted as positive.

3.7.4 Recall - also known as Sensitivity or True Positive Rate, evaluates a model's ability to correctly identify all relevant positive instances in a dataset.

Formula:

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

Where:

True Positives (TP): The number of correctly predicted positive instances.

False Negative (FN): Cases where the model fails to predict the positive class, even though it is present.

4. Result and Discussion

This section discusses the study's findings about enhancing LVB-SVM for improved emotion classification. The results are systematically organized to address the research objectives, while a discussion in greater detail interprets the meaning of these findings in the context of the study. Furthermore, the limitations and implications of the results are critically reviewed to give a holistic view regarding the contributions and relevance of the study.

4.1 Enhanced LBP-SVM Algorithm

To improve the existing algorithm of LBP-SVM for emotion classification, the researcher addresses three main problems stated in Chapter 1. In finding the best value for the hyperparameter, the Grid Search is applied to automatically select the value based on the model's performance, thus saving time and effort compared to manual tuning. Also to enhance the performance of SVM in complex patterns, RFE is used to select the most important features disregarding the least important ones which could introduce noise or redundancy into the model. Lastly, to further improve the performance of the model in emotion classification, the AUs were combined enabling the model to not only recognize texture features but also the distance between facial features, which contribute to the distinct characteristics of emotions.

To assess the model's performance and ensure its accuracy the researcher performs k-fold cross-validation, conducting five (5) tests to evaluate the model's consistency and reliability. K-fold cross-validation (CV) is the most common approach to ascertaining the likelihood that a machine learning outcome is generated by chance, and it frequently outperforms conventional hypothesis testing (Gorriz et al., 2024). The essential configuration parameter for k-fold CV is k, which describes the number of folds in which a given dataset for a machine learning task is partitioned (Nti et al., 2021).

The most common method used to determine the performance of Machine Learning models is Cross-validation. The choice of folds is very important in making sure that the results are reliable, depending on the size of the dataset and the complexity of the model. Though for large datasets few folds would be sufficient, for small datasets, a larger number of folds must be determined to represent the underlying complex behavior of the model. With smaller case files, however, the BN model variant played a role in determining kop: BN models with higher multivariate dependence tended to warrant higher numbers of folds, i.e., kop = 10 in most cases (Marcot & Hanea, 2020). For this study, a value of 10 for k-fold CV will be used to assess the performance of the model.

Table 2: Detailed Results of 10-Fold Cross-Validation for the Existing Algorithm

EXISTING LBP-SVM ALGORITHM					
FOLDS	ACCURACY				
	TEST 1	TEST 2	TEST 3	TEST 4	TEST 5
1	0.4294	0.4663	0.4356	0.3926	0.4172
2	0.4294	0.4110	0.4294	0.4417	0.4417
3	0.4540	0.4110	0.5276	0.4417	0.4908
4	0.4724	0.4847	0.4172	0.4356	0.4172
5	0.4049	0.4172	0.4540	0.4110	0.4417
6	0.4049	0.4663	0.4479	0.4908	0.4847
7	0.4294	0.4356	0.4356	0.5215	0.4233
8	0.4630	0.4444	0.4321	0.3889	0.3951
9	0.4691	0.4136	0.4136	0.5123	0.4383
10	0.4259	0.4444	0.4136	0.4383	0.4753

The table above highlights the accuracy for each of the five tests across folds. The observations shows that while the accuracy across folds is fairly consistent across tests, there are sometimes significant spikes or dips in performance in the given fold. For example, in Test 3, Fold 3 had much higher accuracy than the others and hence an outlier. Such results emphasize the variability of performances across folds and show the need for more optimization. While fold accuracies themselves do not vary wildly, the trends shown in the accuracy plots, indicate as areas of improvement and challenges in the specific folds.

Table 3: Mean accuracy and Standard Deviation of each Test of the Existing Algorithm

Tests	Mean Accuracy	Standard Deviation
1	0.4383	0.0236
2	0.4394	0.0252
3	0.4406	0.0317
4	0.4474	0.0443
5	0.4425	0.0302

The following table summarizes the mean accuracy and standard deviation for each of the five tests. The recorded mean accuracy shows a steady improvement in all the tests, with the highest mean accuracy for Test 4 being 0.4474; however, the standard deviation rises in the later tests, meaning that there is more variability in fold-wise performance. Such an increase may indicate that, as the model's overall performance improves, some folds behave inconsistently. These trends suggest that the model has a potential for a better performance with targeted refinement, particularly in terms of variability among folds.

Table 4: Detailed Results of 10-Fold Cross-Validation for the Enhanced Algorithm

ENHANCED LBP-SVM ALGORITHM					
FOLDS	ACCURACY				
	TEST 1	TEST 2	TEST 3	TEST 4	TEST 5
1	0.9571	0.9877	0.9755	0.9755	1.0000
2	0.9571	0.9755	0.9693	0.9877	0.9816
3	0.9693	0.9693	0.9939	0.9693	0.9632
4	0.9939	0.9939	0.9693	0.9755	0.9877
5	1.0000	0.9448	0.9877	0.9816	0.9571
6	0.9816	0.9877	0.9509	0.9571	0.9693
7	0.9816	0.9755	0.9325	0.9877	0.9387
8	0.9815	0.9691	0.9630	0.9506	0.9444
9	0.9815	0.9753	1.0000	0.9753	0.9815
10	0.9136	0.9568	0.9815	0.9938	0.9877

The detailed results table for the improved LBP-SVM algorithm shows the accuracy for each fold in the five runs of the algorithm. The results show that the model consistently achieves high accuracy, many of them are above 0.9750 in several folds. Some fold achieves 1.0000 accuracy, indicating perfect classification for some of the datasets in certain folds. In addition, values of accuracy hardly go below 0.9500, which emphasizes the robustness of the model to generalize even in complicated emotions. Such a detailed result reinforces the conclusion drawn that the enhanced LBP-SVM algorithm is robust and reliable.

Table 5: Mean accuracy and Standard Deviation of each Test of the Enhanced Algorithm

Tests	Mean Accuracy	Standard Deviation
1	0.9717	0.0234
2	0.9736	0.0140
3	0.9724	0.0193
4	0.9754	0.0129
5	0.9711	0.0191

The table above present the mean accuracy and standard deviation for the five tests, as follows. From all the tests conducted, the mean accuracy ranged between 0.9711 and 0.9754, which marks high performance proficiency in all the tests conducted. The standard deviation values are relatively low, ranging between 0.0129 and 0.0234, hence indicating the stability of the algorithm upon iterations of the test. This further suggests that the algorithm does not really vary the performance significantly among the folds, and, therefore, provides even more credibility to its reliability and robustness

Table 6: Aggregate Classification Report of the 10-fold Cross Validation for the Proposed Enhanced Algorithm

AGGREGATE CLASSIFICATION REPORT				
	Precision	**Recall**	**F1-score**	**Support**
Anger	0.96	0.98	0.97	224
Contempt	0.99	0.99	0.99	90
Disgust	0.98	0.98	0.98	295
Fear	1.00	0.98	0.99	123
Happy	1.00	0.99	1.00	343
Sadness	0.99	0.96	0.97	139
Surprise	0.98	0.99	0.98	413
Accuracy			0.98	1627
Macro avg	0.98	0.98	0.98	1627
Weighted avg	0.98	0.98	0.98	1627

The classification report combines the performance metrics of the model over the 10-fold cross-validation process, and it includes precision, recall, F1-score, and support for every emotion class. The model shows a high precision and recall value, which ranges consistently from 0.96 to 1.00 for all classes, indicating a balanced performance. Macro and weighted averages of precision, recall, and F1-scores are all 0.98, which certifies that the model is highly effective in dealing with the class distribution of the dataset and is able to achieve an overall accuracy of 98%.

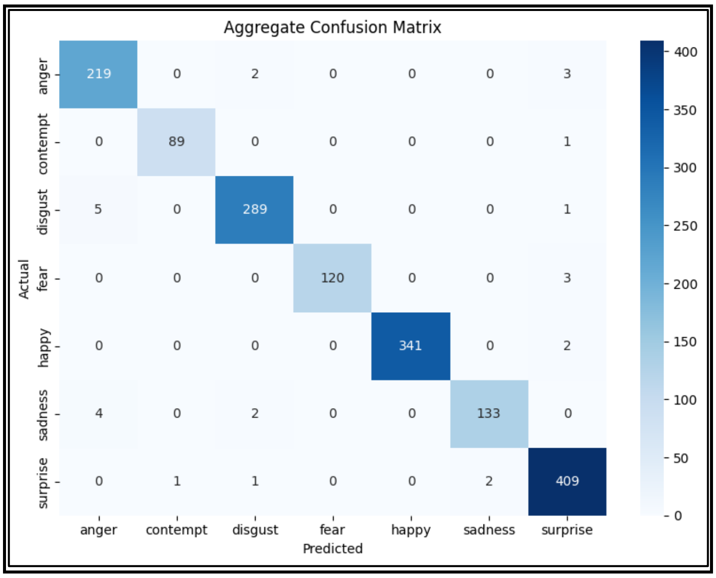

Figure 2: Aggregate Confusion Matrix of the 10-fold Cross Validation for the Proposed Enhanced Algorithm

The heatmap is a visualization of the confusion matrix for the aggregated results of the 10-fold cross-validation. In every cell, the number of instances is shown corresponding to the predicted and actual classes. The diagonal elements are the True Positives and are clearly very high for all classes, which means classification is successful. Their off-diagonal elements, the misclassifications, are minimal. For example, in the "Surprise" class, there are a few misclassified instances to the classes "Anger" and "Contempt," which do not seem significant enough to be considered influential to the overall accuracy. Further robustness is illustrated in the heatmap of the proposed model's high performance with minimum confusion between classes.

5. Conclusions and Recommendations

The study focuses on enhancing LBP-SVM for improved emotion classification by addressing three main limitations of the algorithm: manual hyperparameter tuning, overfitting, difficulties in handling overlapping classes and noisy features, and failure to detect action units. Using the proposed enhancement, the researchers successfully addressed these limitations, improving the performance of the model. The enhanced algorithm achieved an overall accuracy of 98% outperforming the existing algorithm with only 45% accuracy. These results shows the effectiveness of the proposed modifications and their potential contribution to the field of emotion classification.

To further test the robustness of the algorithm, it is highly recommended to apply the improved algorithm to live emotion datasets to test its performance in dynamic, uncontrolled environments. Additionally, it is also crucial to collect larger dataset that captures different facial features across various ethnicities, age, and gender groups for improved generalization and flexibility of the model in classifying emotion across cultures. Further developments may also include the incorporation of other feature extraction techniques like deep learning-based feature embedding to complement LBP-SVM in the detection of subtle emotional cues. Hyperparameter tuning can be further automated using search algorithms like Bayesian Optimization or Genetic Algorithms. Finally, the model’s practical applications in mental health monitoring, customer feedback analysis, and educational technology could help in assessing its broader impact. By following these recommendations, the LBP-SVM algorithm will be further improved and provide a better performance and wider application to emotion classification tasks.

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