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Optimization of Features in Facial Emotion Recognition

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ABSTRACT: The primary goal of machine learning is to develop a model that performs well and predicts accurately in a specific set of instances. We need machine learning optimisation to accomplish this. The process of altering hyper parameters in order to minimise the cost function using one of the optimisation techniques is known as machine learning optimisation. The cost function must be minimised because it describes the difference between the true value of the estimated parameter and what the model predicted. Nonverbal cues conveyed by facial expression play a vital part in interpersonal relationships. The Facial Expression Recognition system is a method of determining a person's emotional state. In this system, the captured image is compared to a trained dataset stored in a database, and the emotional state of the image is shown. This project presents the optimisation of features in facial emotion recognition with the goal of selecting the best and most accurate features for facial emotion recognition via optimisation. Image processing and machine learning are at the heart of this system. We use the Local Binary Pattern to create a comprehensive facial feature description. The Local Binary Pattern (LBP) texture operator is a basic yet very efficient texture operator that labels the pixels of an image by thresholding the neighbourhood of each pixel and treating the output as a binary number. The LBP operator label will be used to create the histogram. The suggested method's recognition performance will be assessed using the trained database and the Support Vector Machine. The LBP descriptor outperforms other well-known appearance-based feature representation approaches in experiments using prototypic phrases. On the JAFFE and COHN-KANADE datasets, we test our suggested technique. Precision, recall, and Fscore from the COHN-KANADE dataset were 83.6142%, 95.0822%, and 88.9955%, respectively, whereas those from the JAFFE dataset were 91.8986%, 98.3649%, and 95.0218%. The experimental findings show that our proposed technique has a competitive classification accuracy.

KEYWORDS: Facial expression recognition (FER), Local Binary pattern (LBP), Support Vector Machine (SVM).

I. INTRODUCTION

As we go from one generation to the next, different technologies are abiding us according to our needs. As a result, we rely heavily on these technologies as part of human-computer interaction. Facial expression recognition is one of them. Faces play a significant part in social communication, as do facial expressions. Facial expressions not only reveal a person's sensitivity or sentiments, but they may also be utilised to judge his or her mental beliefs. Facial expression identification is a technique for recognising facial expressions. A variety of strategies have been proposed to identify expressions such as happiness, sadness, fear, disgust, anger, neutrality, and surprise, while others are difficult to apply. When creating a predictive model, feature selection is the process of minimising the number of input variables. It is preferable to limit the number of input variables in order to reduce modelling computational costs and, in some situations, increase model performance. There are numerous sorts of feature selection algorithms, however they can be broadly divided into two categories: wrapper and filter techniques. Wrapper feature selection approaches generate a large number of models with different subsets of input features and pick the features that result in the best performing model based on a performance metric. Although they can be computationally expensive, these methods are unconcerned with changeable types. A nice example of a wrapper feature selection approach is RFE. Filter feature selection approaches employ statistical techniques to assess the relationship between each input variable and the target variable, and the results are used to choose (filter) the input variables that will be employed in the model. Wrapper Feature Selection: Look for feature subsets that perform well. Filter Feature Selection: Choose subsets of features depending on their proximity to the target.

The Recursive Feature Elimination, or RFE, algorithm is a popular wrapping method. RFE finds a subset of features by starting with all of the features in the training dataset and successfully deleting features until the required number is reached. Fitting the specified machine learning algorithm employed in the model's core, ranking features by relevance, eliminating the least important features, and re-fitting the model achieves this. This procedure is done until

only a certain number of features remain. The difficulty of selecting wrapper features can be presented as an optimisation problem. Find a subset of input features that produces the highest model performance. RFE is one technique to systematically solve this problem, albeit it may be hampered by a high number of characteristics. When the number of features is very large, an alternate option would be to utilise a stochastic optimisation process, such as a stochastic hill climbing algorithm. When the number of features is modest, it may be possible to enumerate all potential feature subsets. Several Input Variables: Enumerate all feasible feature subsets.

Many Input Features: A stochastic optimisation approach is used to locate good feature subsets. Now that we've established that feature selection may be approached as an optimisation problem, let's consider how we might enumerate all possible feature subsets. When creating a predictive model, feature selection is the process of minimising the number of input variables.

It is preferable to limit the number of input variables in order to reduce modelling computational costs and, in some situations, increase model performance. Statistical-based feature selection approaches entail applying statistics to evaluate the relationship between each input variable and the target variable and selecting the input variables having the strongest link with the target variable. Although the choice of statistical measures is dependent on the data type of both the input and output variables, these methods can be quick and successful. As a result, while doing filter-based feature selection, it might be difficult for a machine learning practitioner to choose a suitable statistical measure for a dataset. This chapter will teach you how to pick statistical measures for filter-based feature selection using numerical and categorical data. In that both methods seek fewer input variables to a predictive model, feature selection is similar to dimensional reduction techniques. The distinction is that feature selection chooses which features to maintain or eliminate from the dataset, whereas dimensionality reduction creates a projection of the data that results in whole new input features.

II. RELATED WORK

[1] The channels used to convey the human emotions consider actions, behaviors, poses, facial expressions, and speech. An immense research has been carried out to analyze the relationship between the facial emotions and these channels. The goal of this study is to develop a system for Facial Emotion Recognition (FER) that can analyse the elemental facial expressions of human, such as normal, smile, sad, surprise, anger, fear, and disgust. The recognition process of the proposed FER system is categorized into four processes, namely pre-processing, feature extraction, feature selection, and classification. After preprocessing, scale invariant feature transform –based feature extraction method is used to extract the features from the facial point. Further, a meta-heuristic algorithm called Grey Wolf optimization (GWO) is used to select the optimal features. Subsequently, GWO-based neural network (NN) is used to classify the emotions from the selected features. Moreover, an effective performance analysis of the proposed as well as the conventional methods such as convolutional neural network, NN-Levenberg–Marquardt, NN-Gradient Descent, NN-Evolutionary Algorithm, NN-firefly, and NN-Particle Swarm Optimization is provided by evaluating few performance measures and thereby, the effectiveness of the proposed strategy over the conventional methods is validated.

[2] A novel method for facial expression recognition from sequences of image frames is described and tested. The expression recognition system is fully automatic, and consists of the following modules: face detection, maximum arousal detection, feature extraction, selection of optimal features, and facial expression recognition. The face detection is based on AdaBoost algorithm and is followed by the extraction of frames with the maximum arousal (intensity) of emotion using the inter-frame mutual information criterion. The selected frames are then processed to generate characteristic features based on the log-Gabor filter method combined with an optimal feature selection process, which uses the MIFS algorithm. The system can automatically recognize six expressions: anger, disgust, fear, happiness, sadness and surprise. These selected features were classified using the I Bayesian (NB) classifier. The system was tested using image sequences from the Cohn-Kanade database. The percentage of correct classification was increased from 68.9% for the non-optimized features to 79.5% for the optimized set of features.

[3] This paper proposes a facial expression recognition system using evolutionary particle swarm optimization (PSO)-based feature optimization. The system first employs modified local binary patterns, which conduct horizontal and vertical neighborhood pixel comparison, to generate a discriminative initial facial representation. Then, a PSO variant embedded with the concept of a micro genetic algorithm (mGA), called mGA embedded PSO, is proposed to perform feature optimization. It incorporates a non-replaceable memory, a small-population secondary swarm, a new velocity updating strategy, a subdimension based in-depth local facial feature search, and a cooperation of local exploitation and

global exploration search mechanism to mitigate the premature convergence problem of conventional PSO. Multiple classifiers are used for recognizing seven facial expressions. Based on a comprehensive study using within- and cross-domain images from the extended Cohn Kanade and MM benchmark databases, respectively, the empirical results indicate that our proposed system outperforms other state-of-the-art PSO variants, conventional PSO, classical GA, and other related facial expression recognition models reported in the literature by a significant margin.

[4] John Risch, Shawn Bohn, Steve Poteet, Anne Kao, Lesley Quach, Jason Wu in “Text Visualization” states the importance of Tokenization. They have particularly focused on this part because as we can see the data on the internet exists in the form of unstructured and unorganized text. It is very difficult to find the important context of data. Tokenization allows us to retrieve large quantities of this information with reasonable precision; however, only a tiny fraction of the information available on any given topic can be effectively exploited. Text visualization technologies, as forms of computer-supported knowledge discovery, aim to improve our ability to understand and utilize the wealth of text-based information available to us. These methods attempt to generate summary representations of document collections that convey information about their general topical content and similarity structure, facilitating general domain understanding and analytical reasoning processes.

[5] Nowadays, researchers aim to enhance man-to-machine interactions by making advancements in several domains. Facial emotion recognition (FER) is one such domain in which researchers have made significant progress. Features for FER can be extracted using several popular methods. However, there may be some redundant/irrelevant features in feature sets. In order to remove those redundant/irrelevant features that do not have any significant impact on the classification process, we propose a feature selection (FS) technique called the supervised filter harmony search algorithm (SFHSA) based on cosine similarity and minimal-redundancy maximal-relevance (mRMR). Cosine similarity aims to remove similar features from feature vectors, whereas mRMR was used to determine the feasibility of the optimal feature subsets using Pearson’s correlation coefficient (PCC), which favors the features that have lower correlation values with other features—as well as higher correlation values with the facial expression classes. The algorithm was evaluated on two benchmark FER datasets, namely the Radboud faces database (RaFD) and the Japanese female facial expression (JAFFE). Five different state-of-the-art feature descriptors including uniform local binary pattern (uLBP), horizontal-vertical neighborhood local binary pattern (hvnLBP), Gabor filters, histogram of oriented gradients (HOG) and pyramidal HOG (PHOG) were considered for FS. Obtained results signify that our technique effectively optimized the feature vectors and made notable improvements in overall classification accuracy.

[6] Harris hawk optimization (HHO) is one of the recently proposed metaheuristic algorithms that has proven to be more effective in several challenging optimization tasks. However, the original HHO is developed to solve the continuous optimization problems, but not to the problems with binary variables. This paper proposes the binary version of HHO (BHHO) to solve the feature selection problem in classification tasks. The proposed BHHO is equipped with an S-shaped or V-shaped transfer function to convert the continuous variable into a binary one. Moreover, another variant of HHO, namely quadratic binary Harris hawk optimization (QBHHO), is proposed to enhance the performance of BHHO. In this study, twenty-two datasets collected from the UCI machine learning repository are used to validate the performance of proposed algorithms. A comparative study is conducted to compare the effectiveness of QBHHO with other feature selection algorithms such as binary differential evolution (BDE), genetic algorithm (GA), binary multi-verse optimizer (BMVO), binary flower pollination algorithm (BFPA), and binary slap swarm algorithm (BSSA). The experimental results show the superiority of the proposed QBHHO in terms of classification performance, feature size, and fitness values compared to other algorithms.

III. PROPOSED SYSTEM

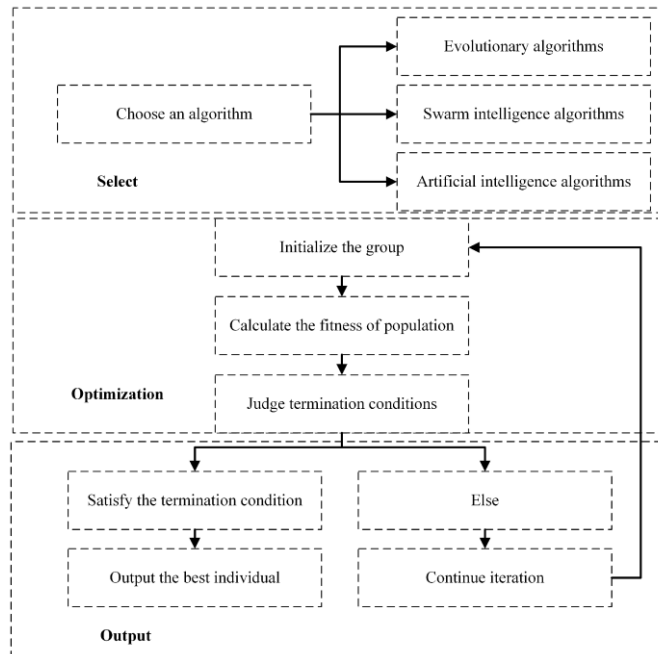


Figure 1. System Architecture

Facial Emotion Recognition is Broad Topic for study and research work but the focusing point for this field is accuracy, effectiveness and uniqueness is most important way to get attention of audience. So basically the reare multiple research work regarding this field but we suggest the proper result for optimizing features for face expression or way to get more accurate, effective and efficient result to the audience. Human Computer Interaction experts are mostly interested in detecting emotions. In addition, several human mental illnesses, such as depressive disorders and anxiety, are related to emotions. As a result, automated emotion detection algorithms must be used for interaction between machines and people. The significant elements for identifying the emotions that are important from one single mode are of ten explored individually by unimodal detection methods.

IV. RESULTS AND DISCUSSION

In the proposed system the system helps to get achievement based on the accuracy, efficiency, effectiveness and speed. As per judgment and research by applying all filters we conclude the result that the Gabor Filter works more precise than other. For each filter accuracy achieved based on 10Epochs. So based on that Gabor Filters works in most appropriate with respective precise, effective and efficient manner. HOG achieved 79% accuracies based on 10 Epochs, LBP achieved 64% accuracies based 10 Epochs, SIFT achieved 92% accuracies based on 10 Epochs, Gabor achieved 97% accuracies based on 10Epochs, and Without feature extraction we achieved 91% accuracies based on 10 Epochs



In [136]: `plot_performance(LBP_history)`

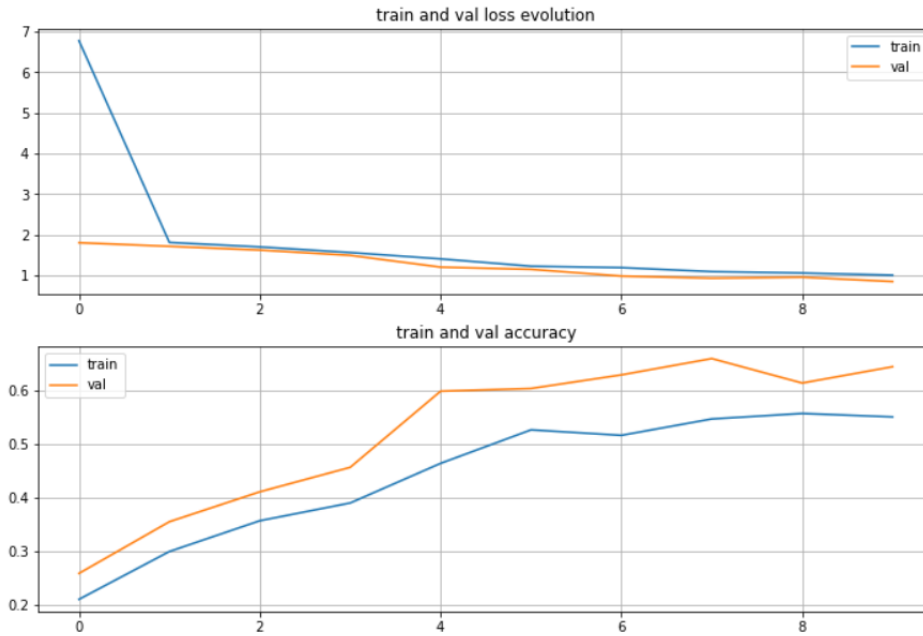


Fig.2 LBP Visualization

In [121]: `plot_performance(HOG_history)`

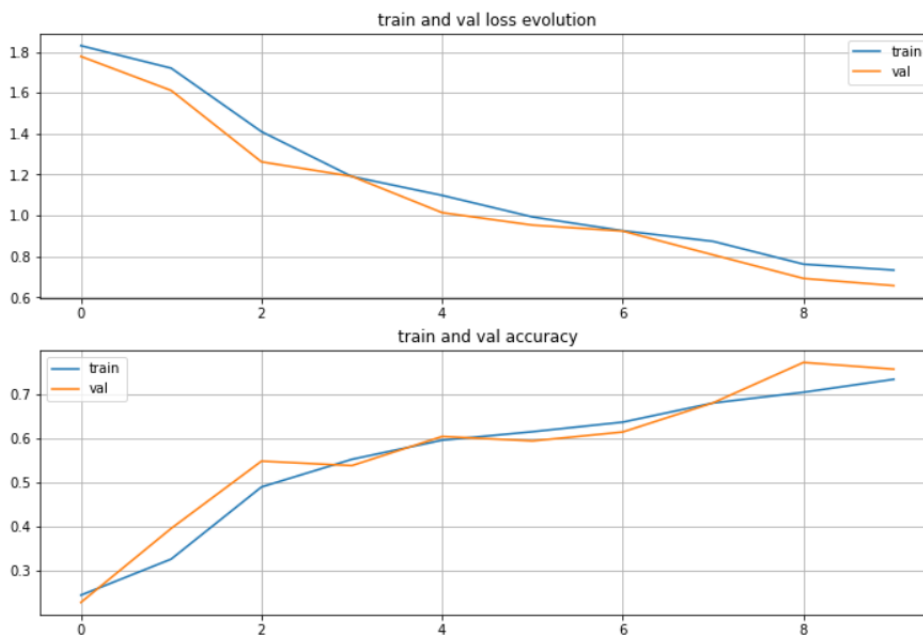


Fig.3 HOG Visualization



In [148]: `plot_performance(SIFT_history)`

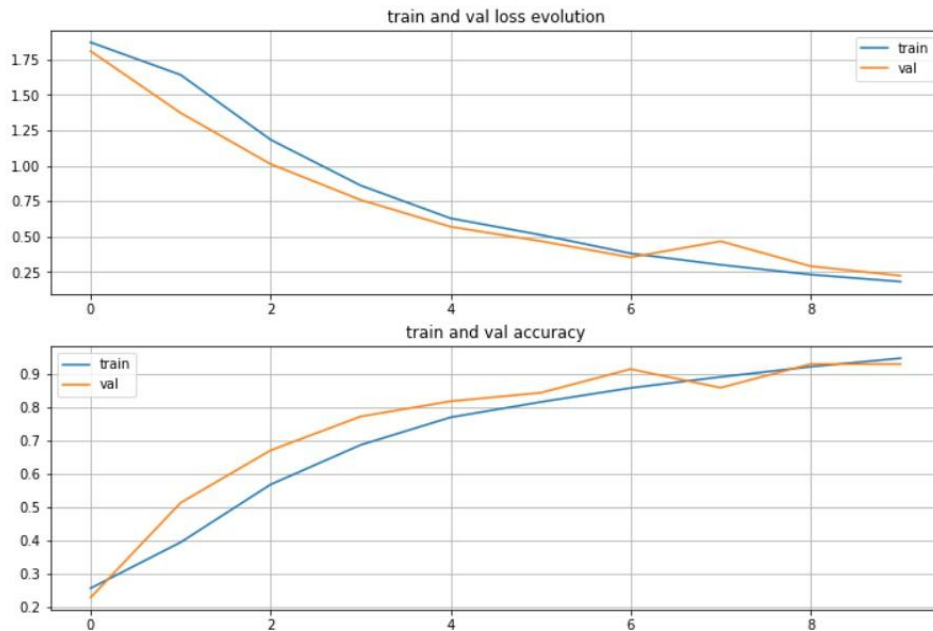


Fig.4 SIFT Visualization

In [81]: `plot_performance(WFE_history)`

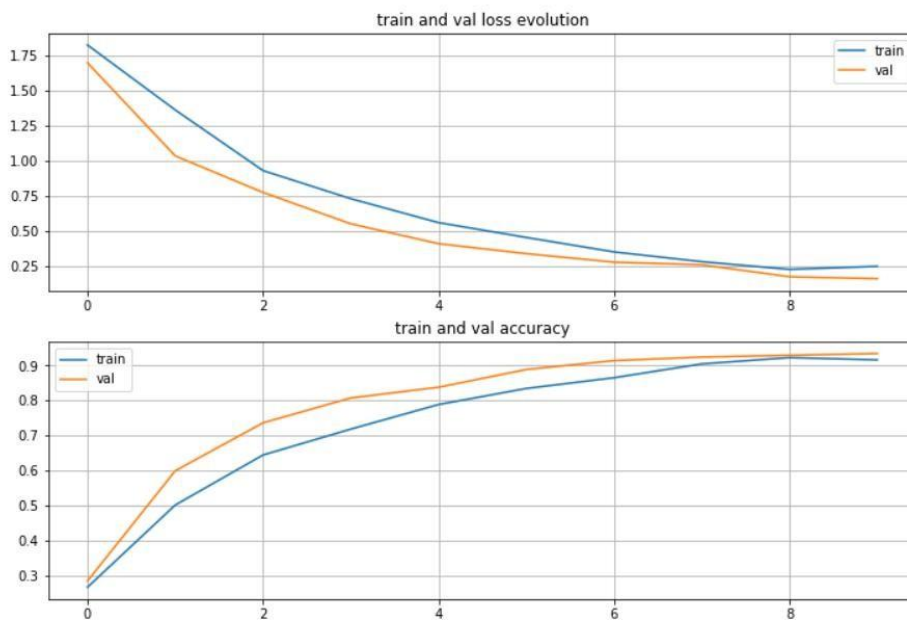


Fig.5 Without feature extraction Visualization



In [76]: `plot_performance(Gabor_history)`

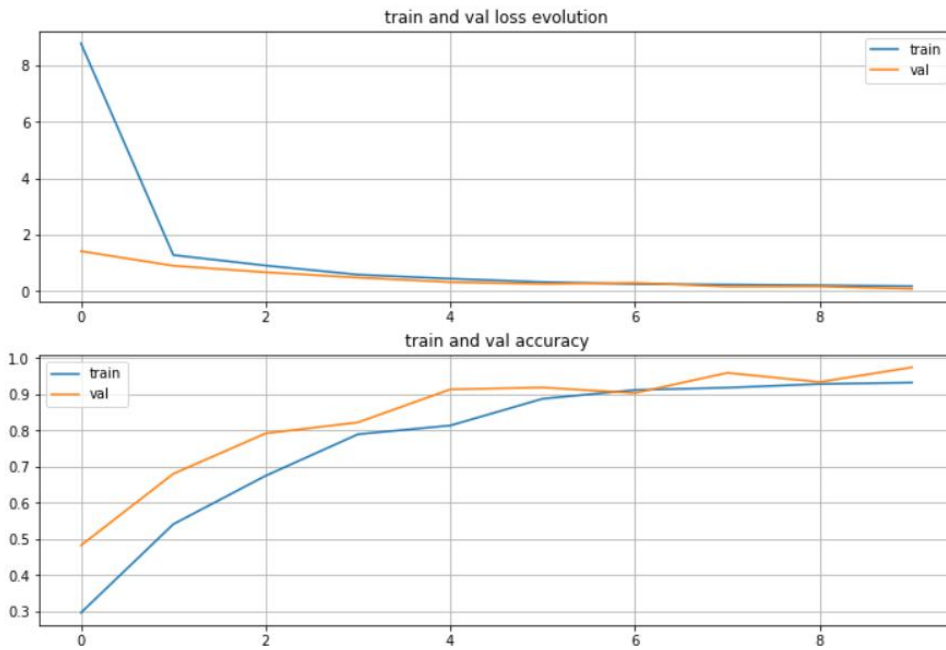


Fig.6 Gabor Filter Visualization

	Accuracies
HOG	0.756345
LBP	0.644670
SIFT	0.928934
Gabor	0.974619
Without Feature Extraction	0.913706

V.CONCLUSION

As we have seen this project will be very beneficial for the people who have to read and evaluate on daily basis. The user can also show the output to higher authorities and can explain them about it within few moments. The project as promised gives a visual representation of data and extracts the important data.

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