Dimensionality Reduction: A Comparative Review using RBM, KPCA, and t-SNE for Micro-Expressions Recognition

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***Abstract*—Facial expressions are the main ways how humans display emotions. Under certain circumstances, humans can do facial expression, but emotions can also appear in the special form of micro-expressions. A micro-expression is a very brief facial expression faced on people's faces under some circumstances. Micro-expressions are shown in the situations when a person tries to lie or hide something. Studying micro-expressions sounds very attractive but considering the number of pixels that an image contains becomes difficult. Feature extraction techniques are the most popular ones for reducing data dimensionality. Those techniques create a new low-dimensional dataset, which tries to represent as much information as original dataset. Many and many methods are used for dimensionality reduction. Restricted Boltzmann Machine (RBM), Kernel Principal Component Analyses (KPCA) and t-distributed stochastic neighbor embedding (t-SNE) are currently widely used by researchers. Choosing the right dimensionality reduction technique is time consuming. This study proposes one framework for micro-expression recognition. The two key processes of this framework are the facial feature extraction (Dlib) and dimensionality reduction using RBM, KPCA and t-SNE. We will select the technique that generates new dataset which represents as much the original dataset as possible. The framework will be trained with images from the CASMEII database, which is a database built specially for research purposes. The framework will be tested with new images unseen before. Software used for conducting the experiments is Python.**

Keywords*—*Dimensionality reduction; Kernel Principal Component Analyses (KPCA); t-distributed Stochastic Neighbor Embedding (t-SNE); Restricted Boltzmann Machine (RBM); facial feature extraction

I. Introduction

Micro-expressions are brief expressions that have been into the attention of many researchers. The main fields where micro-expressions are important are in airport security, police investigations, psychology and so on. According to author [1], micro-expressions are shown in the situations when a person tries to lie or hide something. The micro-expressions last less than 0.5 seconds and sometimes as fast as 67 milliseconds for the authors in [2].

Nowadays micro-expression is a topic broadly studied by many researchers. Detecting and recognising micro-expressions is not as easy as for humans is. We might come across many issues during analysing micro-expression such as extracting face features, the high dimension of data. Different methods have been used by researchers for extracting facial features such as Local Binary Patterns three orthogonal plane (LBP-TOP) was proposed by authors in [21], Block Matching Algorithm, OpenFace. Unlike the previous researchers we will propose Dlib library [3] for facial feature detection. Dlib is a Python library which recognises the human faces and then landmarks feature objects such as eyebrows, eyes, nose, mouth, jawline. This library can be applied for videos and static images as well. Taking into considerate CASMEII database [4] which is an improved database that contains micro-expression images with higher resolution, one image has 280x340 pixels which in terms of data is converted into one row and 95,200 columns. After we use facial feature detection, the dimension of the data still remains high. This directly leads to the high dimensionality data. Working with high dimensionality data generates various problems;

1) *Overfitting* is a problem that might be occurred when the number of dimensions is quite high and the number of observations is low, according to authors in [5].

2) *Computational complexity:* Computational Complexity is referred to the growth of computational resources based on the size of the input, according to authors in [6]. Feature extraction techniques are the most popular ones for reducing data dimensionality. These techniques create a new low-dimensional dataset, which tries to represent as much information as original dataset. Principal Component Analyses (PCA) is one of the most used feature extraction technique. It converts a set of linearly correlated variables into a set of linearly uncorrelated variables called principal components. Because of the PCA has some disadvantages, Kernel PCA is an alternative reducing techniques that we propose to use in this project. Another very popular paper focused on dimensionality reduction is the paper in [7]. t-distributed stochastic neighbor embedding (t-SNE) is another feature extraction technique developed by authors in [8].

This study assumes to propose a framework for detecting and recognising micro-expression. Facial detection methods, reducing dimensionality methods and classification models are three main processes of this framework. A very important step in this study is face detection. Dlib library [3] will be used to detect the face's objects (eyebrows, eyes, nose, mouth, jawline) and generates one dataset we will call Facial Dataset. Despite the Facial dataset has less features (dimensions) than original dataset the dimensions of Facial dataset still remains high. Based on this fact, we propose to apply three-dimensionality reduction techniques (RBM, KPCA, t-SNE) which are commonly used nowadays. Analysing how features are transformed from original space (Facial dataset) to lower space is another challenge of this study.

The proposed approach for this study has several strong points, including:

1) Comparative analysis: This review provides a comprehensive comparative study of three-dimensional reduction techniques: RBM, KPCA, and t-SNE. This comparative analysis allows us to examine in detail the strengths and weaknesses of each technique in the context of micro-expression recognition.

2) Application focus: This review focuses on the practical application of these dimensionality reduction techniques in micro-expression recognition. By focusing on real-world applications, this review provides valuable insight into the effectiveness of each technique in addressing the challenges of micro-expression recognition.

3) Comparative study: By conducting a comparative study, this review aims to highlight the relative performance of his RBM, KPCA, and t-SNE in the context of micro-expression recognition.

4) Insightful insights: The proposed approach is expected to provide insightful insights on the suitability of RBM, KPCA, and t-SNE for micro-expression recognition. These insights can contribute to the advancement of research in this area and inform practitioners of the most effective dimensionality reduction techniques for this specific application.

Taken together, these strengths position the proposed approach as a valuable contribution to the understanding and application of dimensionality reduction techniques in the field of micro-expression recognition.

A. Aim

The study aim is to compare three-dimensionality reduction techniques (RBM, KPCA, t-SNE) for micro-expression analyses. Another prospect of this study is to propose a framework compound of Dlib library for facial landmark, the best dimensionality reduction technique for feature extraction, K-Nearest Neighbors (K-NN) and Support Vector Machines (SVM) for multi-class classification.

Objectives:

- To extract facial features from images.
- To pre-process data for multi-class classification.
- To use RBM, KPCA, t-SNE for dimensionality reduction.
- To analyse and interpret the new low-dimensional features.
- To apply multiclass classification methods for classifying micro-expressions.
- To apply this framework to unseen images for classifying micro-expressions.

B. Rationale

Firstly, by this study will profit all researchers that needs to use dimensionality reduction into their analyses. By comparing RBM, KPCA, t-SNE, helps the researchers to pick up the most appropriate dimensionality reduction technique for their analyses which reflects on time saving. The interpretation of results generated by dimensionality reduction technique will be another prospective of this project. Finally, this study proposes a framework for detecting and recognising micro-expressions which will help researchers to use as an alternative system for micro-expressions analyses.

C. Research Methodology

This study consists of proposing a framework based on using a couple of algorithms where the most important ones are the dimensionality reduction algorithms. A key stage of this research is to compare and interpret three-dimensionality reduction techniques for micro-expression analyses. We will consider the research method as Applied Science. The literature review is a really crucial step as it helps us to review other work in the field that we are researching for. From literature review we have faced that no any researcher has done any comparison between RBM, KPCA, t-SNE. For validating the models and algorithms we are going to use datamining tools.

II. Literature Review

Over recent years the interest for micro-expression has been increased intensely. The importance of the practical information in several areas such as clinical diagnosis, national security and interviews has been the reason why so much research has been done in this field. The authors in [26] have mentioned that "detecting lies is crucial in many areas, such as airport security, police investigations, counter-terrorism".

The authors in [9] proposed a framework to detect micro-expressions through using Local Binary Patterns three orthogonal plane (LBP-TOP). Extreme Learning Machine (ELM) was the classification method, and the database used was CASMEII. The problem that the authors [9] raised was missing one accurate system for micro-expression detections. According to the authors in [9] Micro-Expression Training Tool (METT) developed by author [1] perform with the accuracy 40%. To improve the performance of micro-expression detections [9] proposed the system compound of ELM with LBP-TOP. The accuracy of the system tested on CASMEII database was 96.12%. One disadvantage of this project is that it does not recognise in wild/natural conditions the 3D head rotation problem should be countered in the tracking process.

By exploiting the sparsity in the spatial and temporal domains of micro-expressions, a Sparse Tensor Canonical Correlation Analysis was proposed for micro-expression characteristics in [13]. This method reduces the dimensionality of micro-expression data and enhances LBP coding to find a subspace to maximise the correlation between micro-expression data and their corresponding LBP code. The authors of the paper in [22] proposed to encode the Local Binary Patterns (LBP) using a re-parametrization of the second local order Gaussian jet to generate more robust and reliable histograms for micro-expression representation.

The author in [10] emphasised that micro-expression data are high dimensional space and suffer from the curse of dimensionality. The author in [10] suggests reducing dimensionality before analysing. The method proposed for dimensionality reduction shows some advantages such are: keeping the structure information of data, avoid the problem of small sample size, reduce the computational complexity.

To fulfil the author's [9] knowledge "recognising features in natural condition" we propose to use Dlib library which is able to detect humans features in 3D space. Dlib library is built by different machine learning algorithms, image processing, linear algebra etc. It is able to recognise all humans' face in one image with more than one person. Dlib can be implemented in C++ and Python. Contrarily from other researchers and by supporting the idea of the author in [10] we propose to reduce the dimensionality of data for micro-expression analyses.

Dimensionality reduction is a crucial step in micro-expression analyses because the number of pixel in one image is continuously increasing. Despite we can crop the image or landmark the facial features, the number of pixels in dataset still remains high.

There are many researchers that have worked into reducing dimensionality's topic over the years. Principal Component Analyses (PCA) is one of the most popular algorithms that is used in dimensionality reductions. Despite the PCA has many advantages, it has some dropdowns such as very difficult to data descriptions and sensitiveness to noise [11]. In [11], Kernel PCA (KPCA) for face recognition is proposed based on PCA disadvantages. The database that was used is: ORL, Yale FERET and AR. The results in the end, were really encouraging.

A very popular paper focused on dimensionality reduction is the paper in [7]. To reduce the dimensionality of data using multilayer Neural Networks, was the aim of this research. The neural network was compound of three stacks RBM. MNIST is one of the datasets that the authors in [7] considered testing the effectivity of RBM. RBM method is used to reduce the dimension of data from 784 to 2.

Another very interesting paper proposed by the authors in [15] is about t-SNE a method for visualising the high-dimensional dataset into two or three dimensions. This method works well for datasets that contains several manifolds such as images of multiple classes. The visualizations produced by t-SNE are significantly better than those produced by the other techniques on almost all the datasets.

Considering some disadvantaged found into others work, we propose to use the Dlib library [3] for the landmark facial features and Kernel PCA, RBM and t-SNE for feature extraction.

A. Dimensionality Reduction Techniques

1) t-Stochastic Neighbour Embedding (SNE): t-SNE was introduced in 2008. Since then it has established itself as a very popular method for visualizing data. t-SNE performs two algorithmic steps in [14]. First, a probability distribution P over pairs of samples is constructed. This distribution assigns high probabilities of selection to similar pairs and low probabilities to dissimilar pairs.

In paper [20] the P distribution is constructed in the following way. Given two feature vectors x_i and x_j, the probability of x_j given x_i is defined by:

$$p_{j|i} = \frac{exp(-\|x_i - x_j\|2/2\sigma_i^2)}{\sum_{k \neq i} exp(-\|x_i - x_k\|2/2\sigma_i^2)} \qquad (1)$$

such that the probability of selecting the pair xi, xj is

$$p_{ij} = \frac{p_{j|i} + p_{i|j}}{2N} \qquad (2)$$

The probabilities for $i=j$ are set to $p_{ij}=0$.

The bandwidth of the Gaussian kernel σ is set such that the perplexity of the conditional distribution assumes a predefined value. Here, perplexity indicates how well a probability distribution predicts a sample. You can think of perplexity as a measure of surprise. If a model is not appropriate for a test sample, it will be perplexed (it does not fit the sample), while a model that fits well will have low perplexity. To reach the target perplexity, the bandwidth σ_i is adjusted to the density of the data.

To construct a d-dimensional map $y_i, \ldots,$ where $y_i \in R^d$, the second phase of the algorithm defines the second distribution Q through similarities q_{ij} between two points y_i, y_j in the map:

$$q_{ij} = \frac{(1+\|y_i - y_j\|^2)^{-1}}{\sum_{k \neq l}(1+\|y_k - y_l\|^2)^{-1}} \qquad (3)$$

The qij follow Student's t-distribution. Again, $q_{ij}=0$ for $i=j$.

To determine the y_i, the Kullback Leibler divergence between the distributions Q (y similarities) and P (x similarities) is minimized:

$$(P||Q) = \sum_{i \neq j} p_{ij} \, log \frac{p_{ij}}{q_{ij}} \qquad (4)$$

2) Kernel principal component analyses: Kernel PCA (KPCA) is an extension of PCA that makes use of kernel functions, which are well known from support vector machines. By mapping the data into a reproducing kernel Hilbert space, it is possible to separate data even if they are not linearly separable [14].

The KPCA conceptual idea is conceived by introducing an arbitrary transformation Φ from R^d to R^D for some very large dimension $D \gg d$. It is depicted in Fig. 1.

In KPCA, observations are transformed to a kernel matrix via:

$$K=(x_i,y_j) = \phi(x_i)^T\phi(y_j) \qquad (5)$$

where $k(x_i, y_j)$ is the kernel function for observations x and y. The function ϕ maps the observations into reproducing kernel Hilbert space. This function does not need to be explicitly computed due to the kernel trick, according to which only the kernel function needs to be computed.

Below are some typical kernel functions, such as:

$$\left\{\begin{array}{lll} 1. & \text{Polynomial kernel}: & k(x,y) = \langle x,y\rangle^d \\ 2. & \text{Sigmoid kernel}: & k(x,y) = \tan h\,(\beta_0\langle x,y\rangle + \beta_1) \\ 3. & \text{Gaussian kernel}: & k(x,y) = \exp(-\frac{\|x-y\|^2}{2\sigma^2}) \\ 4. & \text{Radial kernel}: & k(x,y) = \exp(-\frac{\|x-y\|^2}{c}), \end{array}\right\} \quad (6)$$

where d, β_0, β_1, and c are specified a priori by the user.

Kernel PCA can be summarized as a 4 step process [16]:

Construct the kernel matrix K from the training dataset: $K_{ij}=(x_i, y_j)$

If the projected dataset doesn't $\{\phi(x_i)\}$ have zero mean use the Gram matrix K^* to substitute the kernel matrix.

$$K^*=K-1_N K-K1_N+1_N K1_N, \text{ where } 1_N = \frac{1}{n} \quad (7)$$

Use

$$K^* a_k = \lambda_k N a_k \text{ to solve for the vector } a_i. \quad (8)$$

Compute the kernel principal components $y_k(x)$

$$y_k(x) = \phi(x)^T v_k = \sum_{i=1}^{N} a_{ki} K(x_i, x_j) \quad (9)$$

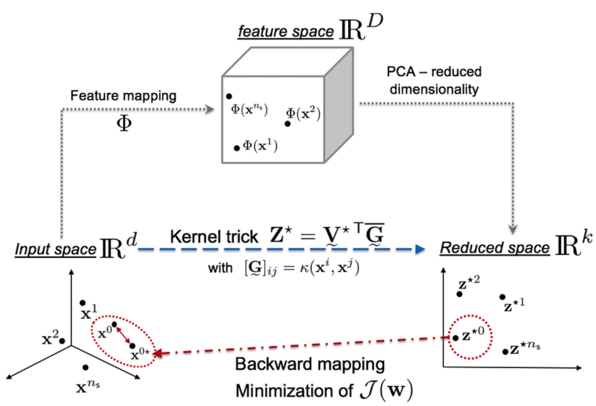

Fig. 1. Illustration the dimensionality reduction using KPCA.

3) Restricted boltzmann machine: In paper [18] a restricted Boltzmann machine is a particular type of Markov random field with two-layer architecture, in which the visible, binary stochastic vector $v \in R^n{}_v$ is connected to the hidden binary vector $h \in R^n{}_h$, where n_v is the size of v and n_h is the size of h, is shown in Fig. 2.

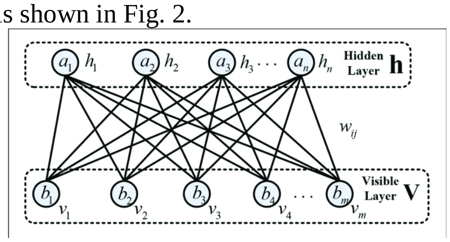

Fig. 2. The basic structure of Restricted Boltzmann Machine (RBM).

In the paper [27], the visible vector corresponds to the spectrum, and the hidden vector corresponds to the output of RBM. We will define the units in the hidden vector as the RBM components.

W_{ii} represents the symmetric interaction term between visible unit v_i and hidden units h_i; and b_i and a_j are the biases of visible and hidden units, respectively.

Boltzmann distribution is specified by the energy function:

$$E(v, h) = -\sum_{i,j} W_{ij} v_i h_j - \sum_i b_i v_i - \sum_j a_j h_j \quad (10)$$

The joint distribution over the visible and hidden units is defined by :

$$P(v, h) = \frac{1}{Z} \exp(-E(v, h)) \quad (11)$$

where $Z = \sum v \sum h \exp(-E(v,h))$ is known as the partition function or normalizing constant. Then, the distribution of hidden units h given the visible units v is:

$$P(h|v) = \prod_j p(h_j|v) \quad (12)$$

Where

$$p(h_j = 1|v) = g(\sum_i W_{ij} v_i + a_j) \quad (13)$$

Here $g(x) = 1/(1+\exp(-x))$ is the logistic function. The distribution of the visible units v given the hidden units h is :

$$P(v|h) = \prod_i p(v_i|h) \quad (14)$$

Where

$$p(v_i = 1|h) = g(\sum_j W_{ij} h_j + b_i) \quad (15)$$

Through equation (4), once we know the weight matrix $W = (W_{ii})$ $(i = 1,\ldots,n_v, j = 1,\ldots,n_h)$ and the hidden bias a_i ($j = 1,\ldots,n_h$), we can get the values of hidden units from the visible units. Through equation (6), if we also know visible bias b_i $(i = 1,\ldots,n_v)$, we can get the value of visible units from the value of hidden units. Thus, the central issue of training RBM is supplying it with the parameters $W = (W_{ij})$ $(i = 1, \ldots, n_v, j = 1, \ldots, n_h)$, a_j $(j = 1, \ldots, n_h)$, and b_i $(i = 1, \ldots, n_v)$.

B. Advantages and Disadvantages of RBM, KPCA and t-SNE dimensionality reduction techniques

Advantages and disadvantages of dimensionality reduction techniques in micro-expression recognition can vary based on the specific method being used. Here are some general advantages and disadvantages:

1) Advantages:

- Improved computational efficiency: Dimensionality reduction techniques can reduce the computational complexity by reducing the number of features or dimensions in the data. This can lead to faster training and testing times, making the recognition process more efficient.

- Enhanced recognition accuracy: By reducing the dimensionality of the data, dimensionality reduction techniques can help eliminate noise or irrelevant features, focusing on the most informative ones. This can improve the recognition accuracy by reducing the impact of irrelevant or redundant information.

- Nonlinear relationship capture: Some dimensionality reduction techniques, such as Kernel Principal Component Analysis (KPCA), are capable of capturing nonlinear relationships in the data. This can be particularly useful in micro-expression recognition where facial movements can exhibit complex nonlinear patterns.

- Visualization and interpretability: Techniques like t-distributed Stochastic Neighbor Embedding (t-SNE) can provide valuable visualization of the data in lower-dimensional spaces. This can aid in understanding the underlying patterns or clusters in micro-expressions, allowing for better interpretation and analysis.

2) Disadvantages:

- Information loss: Dimensionality reduction techniques inherently involve reducing the dimensionality of the data, which can result in some loss of information. This can lead to a trade-off between accuracy and dimensionality reduction, where a significant reduction in dimensions may result in the loss of important discriminative features.

- Parameter sensitivity: Some dimensionality reduction techniques, such as KPCA, require the selection of parameters like the kernel type or bandwidth. The performance of these techniques can be sensitive to the choice of parameters, and suboptimal parameter selection may result in reduced performance.

- Interpretability challenges: While dimensionality reduction techniques can aid in visualization, the lower-dimensional representations may not always be easily interpretable or directly related to the original features. Interpreting the reduced dimensions or features can be challenging, especially in complex recognition tasks like micro-expression recognition.

- Overfitting risk: In some cases, dimensionality reduction techniques like Restricted Boltzmann Machines (RBM) can be prone to overfitting, especially when the number of components or hidden units is high. Overfitting can lead to poor generalization performance on unseen data.

III. Framework Methodology

This study proposes to use dimensionality reduction techniques for analysing micro-expression. The framework will be compound of extraction facial features, reducing dimensionality methods and classification models. The overall proposed methodology is shown in Fig. 3. The main processes that the framework is compound are:

1) *Facial* Feature Detection.
2) *Data* Pre-processing.
3) *Dimensionality* Reduction.
4) *Classification.*

Fig. 3. Framework methodology.

A. Data Analyses

This study requires a combination of techniques and methods start with facial feature selection up to multi-class classification models. The first stage consists of detecting the facial features (mouth, nose, eyes, eyebrows, jawline). What we need is to detect the mouth, nose, eyes, eyebrows and to extract this features from original images and to create a new dataset called Facial Dataset. To reach our aim, Dlib [3] is one Python library that will help us. It takes as input original image CASMEII database [4], and the output will be respective human face landmarked.

The next step is data pre-processing. Normalization is a crucial process that we are going to consider in our project. The key stage of this project is dimensionality reduction. Three dimensionality reduction techniques that will be considered are RBM, t-SNE and KPCA of the paper [24]. Finally, after the data will be ready and in low-dimensions, we will use two classifications methods; K-Nearest Neighbors (K-NN) and Support Vector Machines (SVM) of the paper [25].

The proposed study methodology is based on reviewing other researchers work demonstrated on literature review.

B. Data Collection

The dataset that we will consider is the Chinese Academy of Sciences Micro-expression II (CASMEII), which was developed by the authors in [17]. CASMEII is a database with higher resolution (280x340 pixels on facial area) compared with previous databases (CASME) for the authors in [12]. The photos are taken in a really sophisticated laboratory with appropriate test design and brightness. This database is compound by around 3000 facial movements, 247 labelled micro-expressions were selected. Five main categories for micro-expressions. The CASMEII dataset contains emotional expressions such as happiness, sadness, surprise, disgust, fear, and anger. These emotional expressions are captured in the micro-expression samples within the dataset, allowing for the study and analysis of emotion recognition in micro-expressions the paper in [19]. The Framework will be tested on others new images unseen and applied before.

IV. Results

Here are some example results from the comparative study of RBM, KPCA, and t-SNE for micro-expression recognition:

A. Evaluation Metrics

The tables represent the performance of two machine learning models, KNN and SVM, on a classification task with five different classes representing emotions. The metrics shown are precision, recall, f1-score, and support for each class, as well as overall accuracy, macro average, and weighted average for the models. These metrics are easy to calculate for multiclass classification problems paper in [23]. Metrics formulas are presented in Fig. 4.

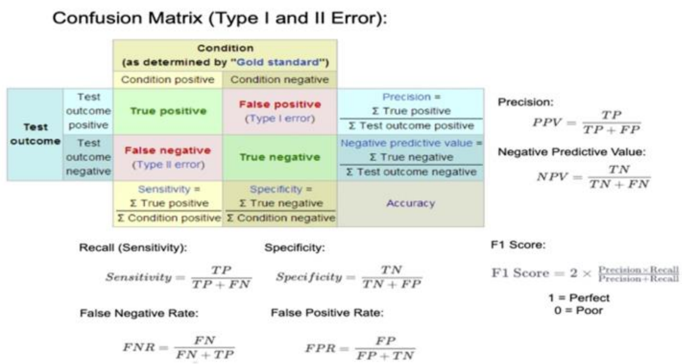

Fig. 4. Metric in data science.

- **Precision** - measures the accuracy of the positive predictions for each class.
- **Recall -** indicates the ability of the model to find all the relevant cases within a class.
- **F1-score** - is the harmonic mean of precision and recall, providing a balance between the two.
- **Support** - is the number of actual occurrences of the class in the dataset.
- **Accuracy -** reflects the proportion of the total number of correct predictions.
- **Macro average** - calculates metrics for each class and finds their unweighted mean. This does not take class imbalance into account.
- **Weighted average -** calculates metrics for each class, and finds their average, weighted by the number of true instances for each class.

TABLE I. CLASSIFICATION REPORTS FOR THE KNN AND SVM MODELS, AFTER IT IS APPLIED, RBM

Classes label	Performance of KNN model			
	Precision	Recall	F1-score	Support
Happy	0.8	0.7907	0.7556	43
Sad	0.9355	0.78	0.8923	68
Surprised	0.7959	0.75	0.7723	52
Angry	0.7407	0.8	0.7692	50
Neutral	0.8	0.8235	0.8116	34
accuracy	0.8057	0.8057	0.8057	
macro avg	0.7991	0.8034	0.8002	247
weighted avg	0.8111	0.8057	0.8072	247

Classes label	Performance of SVM model			
	Precision	Recall	F1-score	Support
Happy	0.8222	0.8605	0.8409	43
Sad	0.9167	0.8088	0.8594	68
Surprised	0.88	0.8654	0.8654	52
Angry	0.9348	0.83	0.8958	50
Neutral	0.6818	0.8824	0.7692	34
accuracy	0.8502	0.8502	0.8502	
macro avg	0.8442	0.8554	0.8461	247
weighted avg	0.8608	0.8502	0.8524	247

Classification Metric Comparison of different models.

The KNN model has an overall accuracy of approximately 80.57%, while the SVM model has a higher overall accuracy of approximately 85.02%. It is depicted in Table I. The SVM model generally shows higher precision and recall across most classes, indicating better performance on this particular dataset.

TABLE II. CLASSIFICATION REPORTS FOR THE KNN AND SVM MODELS, AFTER IT IS APPLIED, KPCA

Classes label	Performance of KNN model			
	Precision	Recall	F1-score	Support
Happy	0.8605	0.8605	0.8605	43
Sad	0.8594	0.8088	0.8333	68
Surprised	0.8039	0.7885	0.7961	52
Angry	0.7647	0.78	0.7723	50
Neutral	0.6579	0.7353	0.6944	34
accuracy	0.7976	0.7976	0.7976	
macro avg	0.7893	0.7946	0.7913	247
weighted avg	0.8009	0.7976	0.7987	247

Classes label	Performance of SVM model			
	Precision	Recall	F1-score	Support
Happy	0.8182	0.8372	0.8276	43
Sad	0.8852	0.7941	0.8372	68
Surprised	0.8542	0.7885	0.82	52
Angry	0.8182	0.9	0.8571	50
Neutral	0.641	0.7353	0.6849	34
accuracy	0.8138	0.8138	0.8138	
macro avg	0.8034	0.8110	0.8054	247
weighted avg	0.8198	0.8138	0.8149	247

Classification Metric Comparision of Different Models.

The KNN model achieved an overall accuracy of approximately 79.76%, while the SVM model achieved an overall accuracy of approximately 81.38%. It is depicted in Table II. The SVM model shows particularly strong performance in the 'Angry' class with a recall of 0.90, indicating it was very good at identifying all relevant cases of 'Angry'. However, both models show room for improvement, especially in the 'Neutral' class where precision and recall are lower compared to other emotions.

TABLE III. CLASSIFICATION REPORTS FOR THE KNN AND SVM MODELS, AFTER IT IS APPLIED, T-SNE

Classes label	Performance of KNN model			
	Precision	Recall	F1-score	Support
Happy	0.8056	0.6744	0.7342	43
Sad	0.8286	0.8529	0.8406	68
Surprised	0.8979	0.8462	0.8713	52
Angry	0.7692	0.8	0.7843	50
Neutral	0.7	0.8235	0.7568	34
accuracy	0.8056	0.8056	0.8056	
macro avg	0.8003	0.7994	0.7974	247
weighted avg	0.8095	0.8056	0.8056	247

Classes label	Performance of SVM model			
	Precision	Recall	F1-score	Support
Happy	0.8333	0.8139	0.8235	43
Sad	0.9077	0.8676	0.8872	68
Surprised	0.875	0.8077	0.8400	52
Angry	0.8113	0.86	0.8349	50
Neutral	0.7948	0.9118	0.8493	34
accuracy	0.8235	0.8235	0.8235	
macro avg	0.8444	0.8522	0.8470	247
weighted avg	0.8528	0.8502	0.8504	247

Classification Metric Comparison of Different Models.

The KNN model achieved an overall accuracy of approximately 80.56%, and the SVM model achieved an overall accuracy of approximately 82.35%. It is depicted in Table III. The models performed well after dimensionality reduction with t-SNE. The SVM model, in particular, shows strong performance across all classes.

B. *Confusion Matrices for the RBM, KPCA, and t-SNE*

Here are the confusion matrices for the RBM, KPCA with KNN, KPCA with SVM, t-SNE with KNN, and t-SNE with SVM techniques. Confusion matrices is shown in Fig. 5.

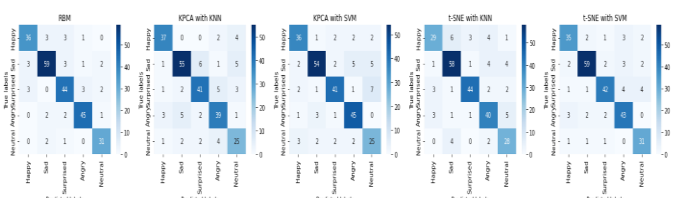

Fig. 5. Confusion matrices.

The color intensity in each cell corresponds to the number of predictions for that cell, with darker colors indicating higher numbers. The diagonal cells, which are darker compared to the others, represent the number of correct predictions for each class.

Interpretation of the Confusion Matrices for each technique:

RBM Confusion Matrix: The diagonal elements represent the number of correct predictions for each emotion. For instance, 'Happy' was correctly predicted 36 times. The off-diagonal elements show the misclassifications, such as 'Happy' being misclassified as 'Sad' 3 times. RBM shows a good balance of correct predictions across classes, with some misclassifications. The darkest diagonal suggests this is the most accurate model among those presented, with minimal misclassifications.

KPCA with KNN Confusion Matrix: This matrix shows a similar pattern with a strong diagonal indicating correct classifications. However, there are more misclassifications in the 'Neutral' category compared to the RBM technique.

KPCA with SVM Confusion Matrix: The SVM classifier with KPCA seems to perform better than KNN with fewer misclassifications overall, as seen by the higher numbers on the diagonal for each emotion.

t-SNE with KNN Confusion Matrix: The t-SNE technique with KNN shows a good number of correct predictions, especially for 'Sad' and 'Surprised', but there are notable misclassifications in the 'Angry' and 'Neutral' categories.

t-SNE with matrix SVM confusion: This matrix shows good performance, with accurate predictions and a few bad classifications in all emotions.

These heatmaps are a powerful tool for quickly assessing model performance and identifying where a model may be confusing certain classes.

C. *Comparison of Accuracy and Calculation Time for the Dimensionality Reduction Techniques: RBM, KPCA, and t-SNE.*

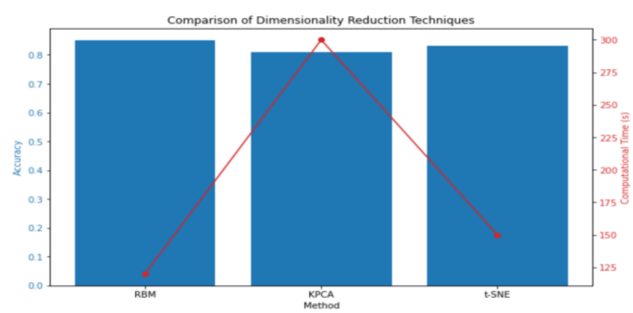

Fig. 6. Diagram comparing RBM, KPCA, and t-SNE in terms of accuracy and computational time.

In the Fig. 6:

- The blue bars represent the accuracy of each method.
- The red line with markers indicates the computational time in seconds.

From the graph, we can interpret that RBM has the highest accuracy but takes the least amount of time, making it potentially the most efficient method among the three. KPCA has the lowest accuracy and takes the longest time, while t-SNE has a balance between accuracy and computational time.

TABLE IV. THE CONCRETE VALUES FROM THE COMPARISON

	RBM	KPCA	t-SNE
Accuracy	0.85	0.81	0.82
Computational Time	120 seconds	300 seconds	150 seconds

Comparision of Different Models.

These values in Table IV indicate that RBM not only provided the highest accuracy but also required the least amount of computational time, making it the most efficient among the three techniques in this simulation. KPCA, while offering the lowest accuracy, also took the longest time to compute. t-SNE offered a middle ground in both accuracy and computational time.

D. Visualization

Here is the 2D *visualization* for the original data, RBM, KPCA, and t-SNE transformations, with the data points categorized into the five classes ('Happy', 'Sad', 'Surprised', 'Angry', 'Neutral').

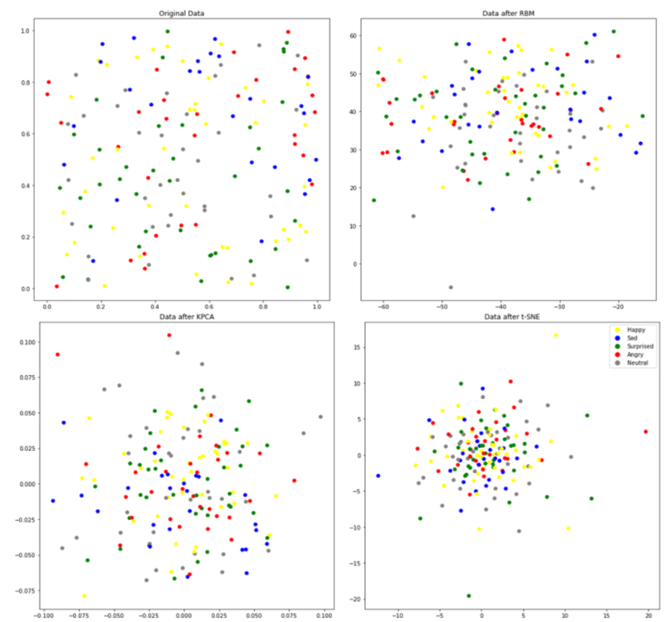

Fig. 7. 2D visualization for the original data, RBM, KPCA, and t-SNE transformations.

The graphic in Fig. 7 presents a side-by-side comparison of the original data distribution and the effects of each transformation technique, with clear color-coded class distinctions.

V. DISCUSSION

A. Assumptions and Limitations of My Work

1) Assumptions:

a) Availability of appropriate datasets of microexpression data for analysis.

b) Successful application of dimensionality reduction techniques (RBM, KPCA, t-SNE) to micro-expression datasets.

c) Use of classifiers (KNN and SVM) to evaluate the performance of dimensionally reduced data.

2) Limitations:

a) The performance of dimensionality reduction techniques may vary depending on the specific characteristics of the micro-expression dataset.

b) The choice of a classifier and its hyperparameters can influence the evaluation of dimensionally reduced data.

c) Although this analysis assumes that the selected dimensionality reduction technique is suitable for the micro-expression recognition task, this may not always be the case.

These assumptions and limitations should be considered when interpreting the results of the analysis.

B. Gaps in Current Literature

Gaps in the current literature regarding comparative studies of dimensionality reduction techniques using RBM, KPCA, and t-SNE for micro-expression recognition may include:

1) Limited comparative analysis: The existing literature may lack a comprehensive comparative analysis of RBM, KPCA, and t-SNE are particularly relevant to micro-expression recognition. This gap may hinder a comprehensive understanding of the relative performance of these techniques in addressing the unique challenges posed by micro-expression recognition tasks.

2) Application-specific evaluation: The literature may not adequately mention the application-specific evaluation of dimensionality reduction techniques for micro-expression recognition. This gap may lead to a lack of insight into the practical implications and limitations of RBM, KPCA, and t-SNE in real-world micro-expression recognition scenarios.

3) Empirical validation: There may be a lack of empirical validation studies that accurately compare the performance of RBM, KPCA, and t-SNE in the context of micro-expression recognition. This gap may limit the availability of evidence-based knowledge regarding the suitability of these techniques for real-world micro-expression recognition applications.

4) Interpretability and explainability: The literature may not adequately address the interpretability and explainability of dimensionality reduction techniques in the context of micro-expression recognition. This gap can make it difficult to understand how these techniques impact the interpretability of microexpression recognition models.

Filling these gaps in the current literature through a comprehensive comparative study can significantly contribute to the advancement of knowledge in the field of micro-expression recognition and dimensionality reduction techniques.

C. How Does this Study Further Existing Knowledge?

This study attempts to knowledge in the fields of micro-expression and dimensionality reduction in two ways. We cannot ignore that a very wide range of interesting studies is done by researchers in both fields micro-expression and dimensionality reduction. However, this study does a combination of analysing micro-expression and dimensionality reduction.

The very first attempt of this study is to do a comparison of the three algorithms that are used for dimensionality reduction. Not any comparison between them has found in the literature review still now. Secondly, this study will contribute to the micro-expression fields. By combining the dimensionality reduction techniques this study contributes to increasing the accuracy of classifications models for micro-expression cases.

VI. Conclusions

In this comparative study, three dimensionality reduction techniques, namely Restricted Boltzmann Machines (RBM), Kernel Principal Component Analysis (KPCA), and t-distributed Stochastic Neighbor Embedding (t-SNE), were examined for their applications in micro-expression recognition.

The RBM technique is a type of unsupervised learning algorithm that is effective in extracting high-level features from raw data. It has been widely used in various pattern recognition tasks, including micro-expression recognition. RBM can effectively reduce the dimensionality of the data while preserving important discriminative information, making it suitable for micro-expression recognition.

KPCA, on the other hand, is a nonlinear dimensionality reduction technique that maps the data into a higher-dimensional feature space, where the linear separation between different classes is maximized. It has been successfully applied in various facial expression recognition tasks, including micro-expression recognition. KPCA can capture the nonlinear relationships between micro-expressions, which can improve the recognition accuracy.

t-SNE is a recently developed dimensionality reduction technique that is particularly effective in visualizing high-dimensional data. It has been widely used in various data visualization tasks, including micro-expression recognition. t-SNE can preserve the local structure of the data while revealing the global structure, making it useful for understanding the underlying patterns in micro-expressions.

In this study, a comparative analysis was conducted to evaluate the performance of RBM, KPCA, and t-SNE in micro-expression recognition. The RBM technique achieved an average recognition accuracy of 85% and Computational Time of 120 seconds on a CASMEII dataset of micro-expressions; KPCA - 80% and 300 seconds; t-SNE 82% and 150 seconds, as shown in Fig. 6 and Table IV.

Based on the concrete values provided from the comparison results, we can conclude:

- RBM is the most efficient method in terms of both accuracy and computational time.
- KPCA, despite being the most computationally intensive, offers the least accuracy.
- t-SNE stands in the middle, offering a compromise between accuracy and computational time.

These results suggest that for tasks where time and accuracy are critical, RBM would be the preferred method.

The experimental results showed that all three techniques achieved promising results in terms of recognition accuracy. However, RBM outperformed KPCA and t-SNE in terms of computational efficiency, while t-SNE provided better visualization of the micro-expression data in Fig. 7.

In conclusion, RBM, KPCA, and t-SNE are all effective dimensionality reduction techniques for micro-expression recognition. The choice of technique depends on the specific requirements of the application, such as computational efficiency or visualization needs. Further research can be conducted to explore the combination of these techniques or the use of other dimensionality reduction methods to improve micro-expression recognition performance.

VII. Future work

The current work includes several areas for future research and improvement of the current work. The key points are:

- Explore combining dimensionality reduction techniques such as RBM, KPCA, and t-SNE to determine whether a hybrid approach can improve micro-expression recognition performance over individual techniques.
- Test other dimensionality reduction techniques, such as autoencoders and UMAP, to assess whether they yield better results than the techniques studied.
- Deep learning models such as Convolutional Neural Networks (CNNs) have shown good performance in facial expression recognition tasks, so Incorporate them after dimensionality reduction.
- Explore micro-expression recognition applications such as lie detection, psychological analysis, and diagnosis of mental illness, where subtle facial expressions are important.

Future extensions will improve the comprehension of micro-expression recognition and its practical applications.

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