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ENHANCED EMOTION RECOGNITION THROUGH HYBRID DEEP LEARNING AND SVM INTEGRATION

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ABSTRACT

The facial expression recognition system, which contributes to the processes to be more effective and faster in many fields such as medicine, education and security, plays an important role in various applications. For example, while emotional and psychological states can be monitored thanks to facial expression recognition in the health field, it can be used in critical applications such as lie detection in the security sector. In education, students' instant facial expressions are analyzed to contribute to the learning processes. The problem of emotion recognition from facial expressions, which is related to many fields, is of great importance in obtaining accurate and reliable results. Therefore, in order to increase the performance of emotion recognition from facial expressions, a hybrid approach combining deep learning and classical machine learning methods is considered in this study. In the proposed method, the ResNet50 model is used as a feature and Support Vector Machines (SVM) is used as a classifier. In this study, a hybrid approach consisting of the combination of ResNet50 and SVM methods is proposed-to increase the performance of emotion recognition from facial expressions. In order to analyze facial expressions, six basic emotions are classified as happiness, sadness, anger, fear, surprise and disgust using the CK+48 dataset. Experimental results show that the proposed hybrid approach has high accuracy in emotion recognition and outperforms traditional machine-learning algorithms.

Keywords: Hybrid model, ResNet50, Support vector machines (SVM), Deep learning.

1 INTRODUCTION

Facial identification is a well-established area in computer vision and artificial intelligence, which is widely applied to protection, user authentication and monitoring systems.

However, beyond identifying the identity, the analysis of facial expressions plays an important role in understanding emotions, psychological states and mutual communication. While traditional facial recognition is aimed at identifying individuals, facial expression recognition (FER) focuses on interpreting emotions based on subtle facial muscle movements.

Words, tone of voice and facial expressions are very important in face-to-face communication between people. It is observed that gestures and facial expressions have a significant impact on interpersonal relationships [1]. These facial expressions carry information about their emotional and psychological states as well as personality reflections [2]. The behaviors of people throughout their lives, a wide range of behavioral patterns from a simple issue to a difficult decision they take are generally referred to as emotional states [3], [4]. It is seen that 6 emotions (happiness, sadness, anger, fear, surprise, disgust), which are considered as basic emotions, are generally accepted and mutually used in every environment related to life and by people in these environments [5].

Emotion recognition from facial expressions facilitates various processes in many fields, especially in medicine, education and security [6]. It is seen that it will be used in platforms where various physical and mental diseases are detected in the field of health and direct or alternative suggestions are given for healthy life, in achieving success with the instant facial expressions and reactions of students in the field of education, in the field of security, in cases such as lie detection in investigations, etc. It is seen that it will contribute to increasing the success percentages in many sectors with these examples. [7], [8]. Therefore, within the scope of this study, a face recognition system with artificial intelligence, which is useful in many fields, has been studied.

Additionally, comprehensive experiments have been conducted to thoroughly evaluate the performance achieved by utilizing different features with various classifiers in the facial expression recognition problem. These experiments have been systematically categorized into three main groups: classical machine learning classifiers, which rely on handcrafted features, hybrid approaches that combine deep and traditional feature extraction techniques, and deep learning methods, which automatically learn hierarchical representations from data. This categorization allows for a detailed comparative analysis, highlighting the strengths and limitations of each approach in enhancing facial expression recognition accuracy. The general structure of the study is explained in the section Materials and Methods, where information about the features and classification methods is given. In Results and Discussion section, information about the experimental results obtained within the scope of the study is given and in the last section, the study is concluded.

2 RELATED WORKS

Facial expression recognition applications consist of two basic steps: feature extraction and classification [9]. In many areas, high-performance values have been achieved by obtaining much stronger features by using hybrid features. There is a significant increase in classifier performance with the acquisition of strong features [10]. These studies are generally used in combination with feature extraction and classical machine learning methods or deep learning methods. In the study conducted by Li and Lima [11], to overcome the limitations such as the low generalization ability of network models and weak robustness of recognition systems, the features obtained using deep residual network ResNet-50 were combined with Convolutional Neural Networks (CNN). Experimental results show that the proposed method increases the success rates. In the study conducted by Bayrakdar et al. [12], The authors analyzed 4 different emotions (sadness, happiness, surprise, neutrality) of individuals through pre-created video files and reduced the number of image frames in these video files. They developed an advanced facial expression recognition system for video files thanks to threads in parallel with each other on a computer with high processing power and capacity. In the method proposed by Mukhopadhyay et al. [13], three different textural image features, namely Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Completed Local Binary Pattern (CLBP), which are sensitive to changes in facial expressions, were used. These features were used with the Convolutional Neural Network (CNN) model and more accurate results were obtained Sadeghi et al. [14] developed a new deep learning model, HistNet, for facial expression recognition. HistNet aims to increase accuracy by using histogram-based feature extraction instead of superficial information in the facial expression recognition task. In the study by Karnati et al. [15], feature extraction modules were applied regionally and structurally to detect distinctive features. Thanks to this method, they obtained a high-performance value for the dataset used. In Haq et al.'s study's study, convolutional neural networks (CNN) were used to analyze the universal emotional states of individuals in real-time [16]. As a result of this study, higher performance was obtained compared to the studies performed in real-time.

In order to contribute to the above-mentioned areas, this study aims to achieve a more successful classification performance by using robust features. To obtain robust features, some experiments were carried out on the dataset and classification was performed using feature extraction and machine learning methods. In order to measure the performance values of the study, the CK+48 dataset was used as the dataset in this study. In this dataset, there are six class labels: happiness, sadness, anger, fear, surprise and disgust In this study, classical machine classifiers, deep learning methods and hybrid approaches were used. Thanks to the proposed methods, it is seen in line with the data obtained from the experimental results that the classification performance has increased.

3 MATERIALS AND METHODS

In this study, deep learning methods, classical machine classifiers and hybrid approaches are used to identify emotions from facial expressions. The hybrid approaches can be divided into two subcategories. In the first sub-category of hybrid approaches, classical features such as Scale-invariant feature transform (SIFT) and KAZE are used in the feature extraction step and deep learning methods are used in the classification step. In the second subcategory, features obtained from deep learning methods are used as features and classical machine classifiers are used as classifiers. This structure is given in Figure 1.

In the experiments, all machine learning and deep learning methods were used with their default hyperparameter settings as provided by the respective libraries. No manual tuning was performed for hyperparameter optimization. For instance, the Support Vector Machine (SVM) classifier was employed with the default radial basis function (RBF) kernel in the scikit-learn library. Similarly, other classifiers, including XGBoost, Random Forest, and Logistic Regression, were utilized with their standard parameters. Regarding deep learning-based feature extraction, the pre-trained ResNet50 models were applied without modifying their original configurations. This approach ensures that the results reflect the baseline performance of each method without additional optimization.

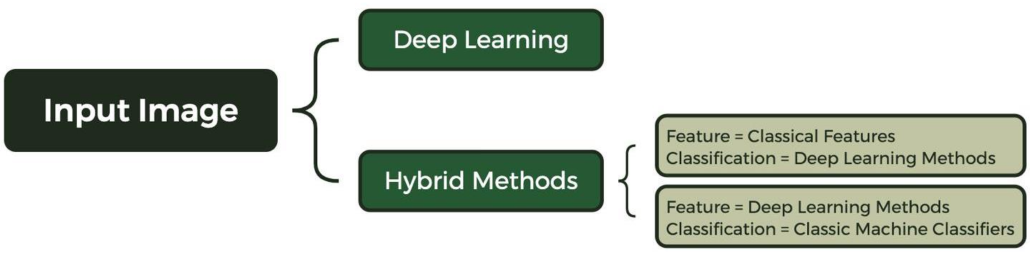

Figure 1. The general structure of the study.

In the designed system, Convolutional Neural Network (CNN), Scale-Invariant Feature Transform (SIFT), Visual Geometry Group 16 (VGG16), Residual Network 50 (ResNet50) and KAZE, methods are used for feature extraction, while Convolutional Neural Network (CNN), Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), Radial Basis Function (RBF), and Logistic Regression (LR) methods are used in classification stages. With the input of the images in the data set, features are extracted and then the classifier is trained. After this process, the features extracted from the test data are classified with the test data. The methods used in the study are given in Figure 2. As a result of the experiments, the highest performance was obtained from the application in which the feature obtained with the Resnet50 deep learning method was used together with the SVM classifier. Data set, performance metrics, Resnet50 deep learning method and SVM classifier used in the proposed method are given in detail below.

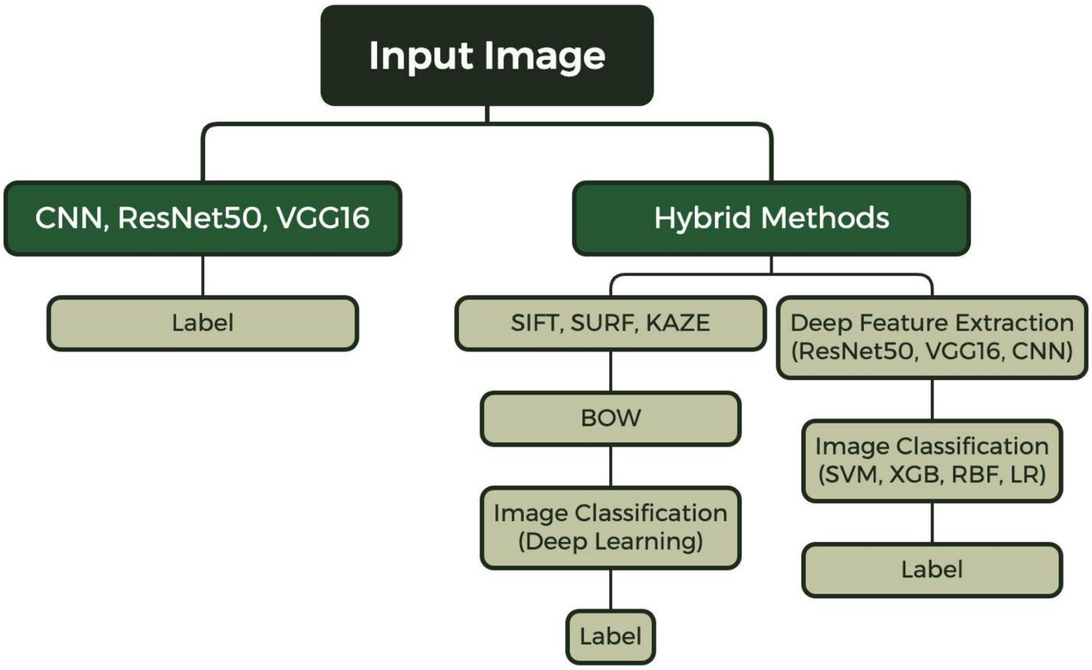

Figure 2. The methods used in the study.

3.1 Data Set

To analyze the emotion from facial expressions, the ‘CK+48’ dataset [17] was used in this study. This dataset was chosen because it is considered a well-organized and widely used standard in the field of facial expression recognition. Since it contains high-quality and clearly labeled facial expressions collected in a controlled environment, it allows for the accurate evaluation of the proposed method without the uncertainties that may be caused by environmental factors. The primary goal of this study is to evaluate the effectiveness of the proposed combined approach rather than addressing the difficulties related to spontaneous or natural expressions. Therefore, the CK+48 dataset is considered a suitable starting point to measure the basic performance of the method. Larger and more diverse datasets collected in real-world scenarios, although they contain a wider range of facial expressions, bring with them additional challenges such as high computational costs, obstacles, and variability. Domain adaptation techniques, extensive data augmentation, or transfer learning strategies are usually required to increase generalizability. However, since this study mainly focuses on the development of the method, a widely used reference dataset, CK+48, was preferred for preliminary evaluation. In this dataset, there are images containing six human emotions (happiness, sadness, anger, fear, surprise, disgust). In the 'CK+48' dataset, there are '981' images. These images consist of 48x48 grey images. The images in the dataset are generally obtained from video frames and have not undergone much change [18]. Figure 4 shows sample images of the dataset.

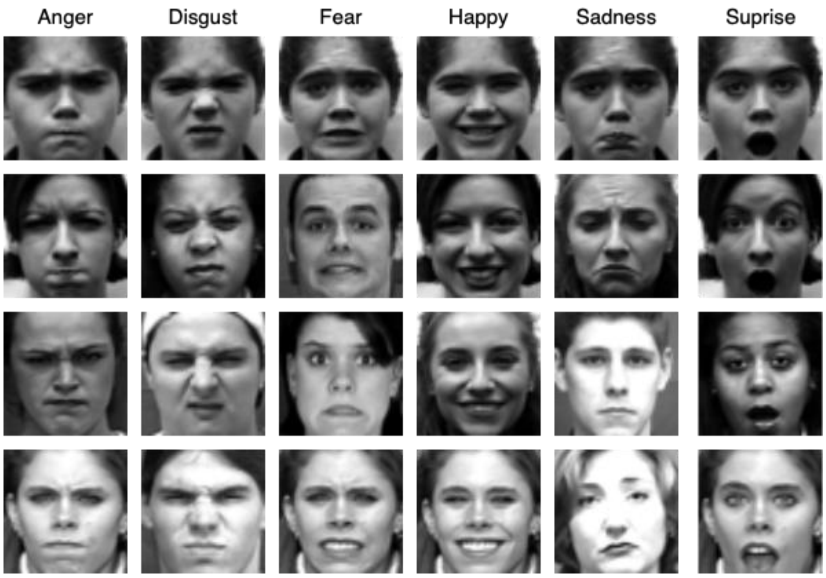

Figure 3. Sample images of the CK+48 dataset.

3.2 Performance Metrics

In order to evaluate the performance of this study, recall, precision, and F1 scores were used. These metrics are determined according to the total number of true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN). The equations of Accuracy, Recall (R), precision (P) and F1 score metrics are given in Equation 1-4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall\ (rc) = \frac{TP}{TP + FN} \tag{2}$$

$$Precision\ (pr) = \frac{TP}{TP + FP} \tag{3}$$

$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{4}$$

3.3 Resnet50

When the layers of CNN architectures developed in the past are modified, the problem of gradient disappearance arises and the layers become non-scalable. As a result of this problem, the non-scalable layers will reach saturation with each layer added as a result of repeated operations and the performance will deteriorate. To solve this problem, ResNet architecture is built by combining blocks into layers. ResNet prevents the gradient vanishing by increasing the depth values of the network and preserving feature representations. In the ResNet architecture, jumping between connections can be done with a method called jumping or identification of connections. This method adds the input value of the layer behind to the output value of the layer ahead by skipping the other layers in between. With this method, the intermediate corrupted layers and the redundant convolutional layers are connected [19].

ResNet50 is obtained by replacing the 2-layer blocks in the network consisting of 34 layers with a 3-layer bottleneck block. This three-layer structure has dimensions of 1×1, 3×3 and 1×1. Layers with 1×1 dimensions change the values of the dimensions by increasing and decreasing. In the layer with 3×3 dimensions, it creates a small-sized bottleneck for input/output. In this way, the training speed of each layer is much faster.

Deep learning models can have higher generalization capacity when pre-trained on large datasets. However, since the data specific to a particular application is usually limited, the transfer learning method can yield more successful results by re-using a model trained on a large-scale dataset as a feature extractor [20]. In this study, the pre-trained ResNet-50 model is used for feature extraction, and then these features are processed with a traditional machine learning classifier, SVM.

3.4 Support Vector Machines (SVM)

Support vector machines (SVM) is a machine learning technique that is widely used in classification procedures, although it has been used in the literature for regression analysis and classification. This approach is based on a supervised learning model. While executing the algorithm, kernel functions can be used depending on the structure and type of the processed data [21], [22]. Therefore, linear or non-linear classification processes can be performed by SVM. Support vector machines find the hyperplane that discriminates the data of the training with maximum margin and the samples are classified by means of the learned hyperplane. Structural risk minimization is the basis for the use of hyperplanes with maximum margins [23].

Example of linearly separable training for the primary optimization problem with fixed margins; $S = ((\overrightarrow{Xi},\ y_1\ ) \ldots, (.\overrightarrow{Xi}, y_i\ ))$ and hyperplane $(\overrightarrow{W}, b)$, the solution of this problem is solved by the following equation 5. Minimum subtraction

$$y_1 \left[\overrightarrow{W}.\overrightarrow{Xi} + b\right] \geq 1, i = 1, \ldots, l \tag{5}$$

The lower plane of the edges is thus maximized.

Due to the primary optimization problem given above, the use of kernels becomes necessary and a high-dimensional feature space is used. The training examples are binary only as internal products and therefore do not need to be represented as feature vectors as long as training is in progress, nor do they need to be represented in the testing phase (Deisenroth, Faisal, & Ong, 2020).

Example of linearly separable training for the secondary optimization problem with fixed margins; $S = ((\overrightarrow{Xi}, y_1) \ldots, (.\overrightarrow{Xi,}, y_i))$ and $\overrightarrow{a^*}$ If it is assumed to be, the solution of this specified problem is solved using the following equation 6. Maximum subtraction

$$W\left(\overrightarrow{a^*}\right) = \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} y_i, y_j, a_i, a_j, \overrightarrow{x}_i, \overrightarrow{x_j} \tag{6}$$

Then the weight vector $\overrightarrow{a^*} = \sum_{i=1}^{l}, y_i\ a_i * \overrightarrow{x}_i$ hyperplane with maximum margins is obtained.

4 RESULTS AND DISCUSSION

When the experimental results of the method proposed in this study are categorized, two main categories are formed. If these two categories are explained, the first category includes the experiments performed with deep learning methods, and the second category includes the experiments performed by combining deep learning methods and the methods used in classical machine classifiers.

CNN, VGG16 and ResNet50 methods, which are frequently used in the literature, are also used in this study to obtain performance data. Finally, inspired by the studies indicating that more successful results are obtained with the use of hybrid approaches in various fields [25], applications have been developed by using the methods in deep learning and classical machine classifiers as a hybrid. For this purpose, features were extracted using ResNet50, VGG16 and CNN deep learning methods. The obtained features were classified with SVM, XGB, LR and RF classifiers. In addition to these, the experimental results using SIFT, SURF and KAZE features in the feature extraction step and CNN deep learning method as the classification method are given in Table 1 and Figure 5.

Table 1. Performance results of the experiments performed on the CK+48 dataset.

Features	**Classifier**	**Precision (%)**	**Recall (%)**	**F1 (%)**	**Accuracy (%)**
CNN	SVM	3.63	14.29	5.78	25.38
	XGB	59.37	55.50	56.92	59.94
	RF	45.55	33.91	35.96	38.74
	LR	3.63	14.29	5.78	25.38
Resnet50	SVM	100.00	100.00	100.00	100.00
	XGB	95.66	93.76	94.62	95.62
	RF	96.44	94.19	95.16	95.51
	LR	97.57	97.95	97.74	98.17
VGG16	SVM	99.08	98.46	98.75	99.08
	XGB	98.48	97.94	98.17	98.47
	RF	98.72	97.14	97.87	98.37
	LR	99.43	99.03	99.22	99.49
CNN	CNN	91.91	93.92	92.81	94.58
ResNet50	ResNet50	64.35	62.40	62.32	71.86
VGG16	VGG16	94.32	95.70	94.80	95.25
SIFT	CNN	89.87	83.85	85.99	89.15
SURF	CNN	72.41	69.65	69.94	76.27
KAZE	CNN	87.54	78.60	80.86	86.78

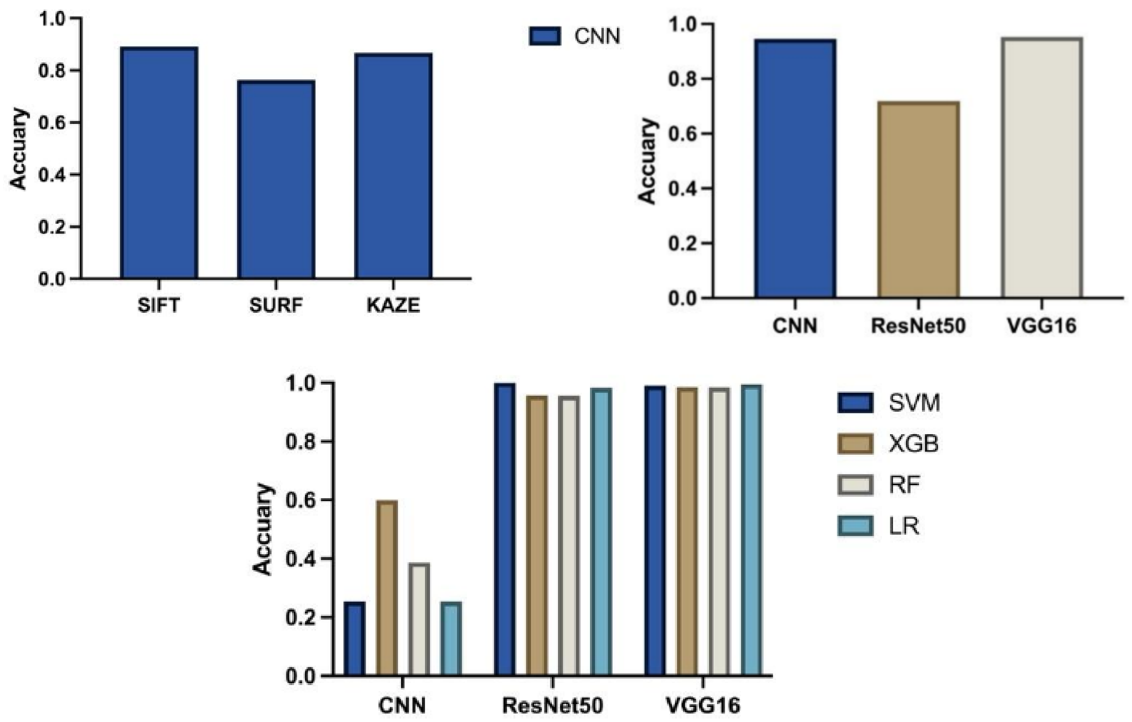

Figure 4. Graphs of experimental results.

As seen in Table 1 and Figure 5, the most successful method is the hybrid approach, which combines ResNet50 and SVM methods. Table 2 compares the proposed method's performance with studies developed using the CK+48 dataset in recent years.

Table 2. Performance results of the experiments performed on the CK+48 dataset.

Research	Methods	Accuracy (%)
Liu and Yue [26]	CNN-LSTM	84
Owusu and Wiafe [27]	Ada-AdaSVM	91.28
Syalomta et al. [28]	NNN-Net	98.63
Deepan et al. [29]	Gabor + CNN	99.43

As seen in Table 2, the proposed hybrid approach, which combines ResNet50 for feature extraction and SVM for classification, outperforms previously developed methods. While Deepan et al. [28] achieved an accuracy of 99.43% using a Gabor filter and CNN combination, our proposed method reached a perfect accuracy of 100%. This improvement can be attributed to the use of robust deep features extracted by ResNet50 and the high generalization capability of SVM. Unlike traditional CNN-based methods, our approach benefits from a more effective feature representation.

Although the proposed hybrid approach combining ResNet50 and SVM achieves high accuracy in emotion recognition, certain limitations are observed. One notable limitation is the use of the CK+48 dataset, which consists of well-posed and controlled facial expressions. This may lead to difficulties in generalizing the model to real-world scenarios where changes in lighting, occlusions, and spontaneous expressions are present. Additionally, the model may perform poorly in cases where facial expressions are ambiguous, which may lead to potential misclassifications. To partially address this limitation, the method was also evaluated on the JAFFE dataset, which includes more varied lighting conditions and facial expressions. The results obtained from the JAFFE dataset demonstrated an accuracy of 100%, indicating that the proposed approach maintains a reasonable level of performance even under less controlled conditions. Future work could focus on including more diverse datasets and integrating advanced augmentation techniques to improve robustness.

5 CONCLUSION

In this study, a new hybrid approach is used to analyze emotion from human facial expressions. While performing emotion detection from facial expressions, hybrid methods obtained by combining these two methods are used in order to obtain higher performance results compared to classical machine classifiers and deep learning methods. The CK+48 dataset and 981 images were used to test the application performed within the scope of the study. According to the results of the experiment, the recognition success of emotions was determined as 100% thanks to the method obtained by combining ResNet50 and SVM methods. Compared to existing methods (as shown in Table 2), our proposed hybrid approach achieves state-of-the-art performance, demonstrating the effectiveness of combining deep feature extraction with classical machine learning classifiers. In future studies, we aim to achieve higher performance with new methods developed on datasets containing different images and classes.

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Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

Muhammed Kerem Türkeş contributed to the experimental studies and preparation of the article.

Yıldız Aydın contributed to the experimental studies, interpretation of the data and management of the study.

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