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AN INTELLIGENT SYSTEM FOR EMOTIONAL AND PSYCHOLOGICAL DISORDER DETECTION VIA FACIAL FEATURE ANALYSIS

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Abstract
Depression is a common mental disorder that can have a big effect on people's daily lives. The detection of depressive disorder and other facial emotion recognition disorders plays an important role in identifying psychological disorders through facial features. The manual diagnosis process is time-consuming and hard for doctors. Therefore, many researchers have proposed computerized techniques for detecting these disorders. However, images can be analyzed for diagnosis. Deep convolutional neural networks (CNNs) have demonstrated impressive performance in different computer vision tasks. Many researchers suggest that machine learning techniques can be used to analyze emotional images, such as own syndrome images, to assist in the detection of disorders. Additionally, machine learning techniques can be used to analyze time-series data, such as videos, to detect changes in depression and facial emotion features over time. Facial emotional images may be of poor quality due to factors such as poor lighting or camera movements, which can make it difficult to accurately detect depressive disorder and facial emotion indefinitely. In this research, we have used computer vision-based techniques to detect are classify depressive disorders and facial emotion recognition. We used facial emotion datasets such as FER-2013, CK+, and JAFEE for training deep learning AlexNet model, but the results were not satisfactory, and then the AlexNet is used with classifiers by combined layer (fc6, fc7, fc8). The proposed method obtained 92.60% accuracy on the FER-2013 dataset. Our proposed method is better than existing methods because it identifies the facial features from any type of image provided.

Keywords: Depression, Emotions, Classification, Deep Learning, Disorder

Introduction
Depression is a common and serious mental health disorder that affects more than 264 million people around the world (World Health Organization [WHO]). It is one of the leading drivers of disability, resulting in misery for individuals and ruin for families and society as a whole. Depression, if not evaluated and treated in a timely manner, can cause devastating effects, including social isolation, physical illnesses, and even suicide. It is estimated that by 2030,

depression will be the primary culprit of disability worldwide [33]. Given the increasing prevalence of depression and the shortage of relevant mental health professionals, the need for more scalable, cost effective, and automated assessment and diagnosis has never been more pressing.

The traditional clinical diagnosis of depression based upon clinical interviews, observations of behaviour, and psychological questionnaires is certainly effective; however, the assessment is a subjective process that is very time consuming in both its implementation and the time for diagnosis, and often unaffordable, particularly in under-resourced areas. Thus, researchers are turning toward artificial intelligence (AI) and computer vision technologies for automatic early detection of depression. Facial Expression Recognition (FER) is a potential method in this paradigm, by which facial movements and expressions can provide valuable data regarding the emotional and psychological state of an individual.

Facial expressions are a natural and powerful way to communicate human emotion. The range of emotions that the human face can express is immense, and small changes in facial muscles can betray stress, sadness, or other indicators of depression. FER consists of three major steps: detecting the face in an image or video, extracting the facial features, and classifying the emotional state. The recent introduction and successes of deep learning, specifically Convolutional Neural Networks (CNN's), have greatly increased accuracy in FER system classifications. The strength of CNN's lies in their ability to acclimatize facial information and learn other complex patterns, including unique lighting, foreground and backgrounds, and poses that occur in the real-world context [5].

Although key advances have been made in recognize depression through FER systems, many issues persist. Though much work remains to be done to maximize accuracy in detecting depression, each case will deteriorate due to low-resolution digital images, occlusions, facial masks and neutral expressions. Additionally, people with depression may suppress their facial expressions, inhibiting the models ability to "see" potential emotional cues in depression. Improvements to the training datasets which are used will enable better models for helping a wider range of people with mental health issues, but it is essential that datasets are not only larger, they need to be robust, adaptable and diverse and supplemental methods for feature extraction need to be developed [32].

The stated study investigates how to combine FER and facial feature identification algorithms to enhance the accuracy in the field of depression detection models. By implementing cutting-edge deep learning practices on benchmark datasets, an exploration like this can further support the existing commitment towards building more accurate, non-intrusive, real-time, and accessible mental health monitoring tools.

Recently, facial emotion recognition (FER) has progressed in deploying multiple models, using a wide variety of datasets, with important applications. For instance, studies using the FER-2013 dataset (Ansari et al., 2023) discussed the performance of Xception models with pre-processing achieving 67% accuracy [2]. While Bhogan et al. (2023) presented a better

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performance on the FER-2013 dataset, using CNN classifiers [8], Agarwal et al. (2022) employed tensor flow based CNN models and demonstrated a 95% accuracy [1]. Bukhari et al. (2022)'s study had excellent predictions using Inception-V3, achieving 97.93% accuracy [10]. Also, ensemble modelling methods, such as the ones utilized by Shirsath et al. (2022), showed a close performance to that of other models - with CNN models outperforming all models proposed [41]. Moreover, these challenges regarding emotional recognition are profound and especially troubling are sad and fearful components, as noted by Reddy et al. (2021) [37].

Based on the CK+ dataset, studies such as those principle studies described by Das and Neelima (2023) [13] and by Bisogni et al. (2022) [19] in their studies measuring accuracy above 90%, using CNN's and transfer learning techniques, demonstrated their effectiveness. There were also JAFEE dataset-based models, such as Jaiswal et al. (2020) [21], that showed accuracy using models which has been modified, which can be important and gives options. Private datasets have yielded different results; however, with hybrid networks and CNN-based approaches shown good learning rates across a span of facial expression recognition systems. In general, the studies discussed show further evidence of the ongoing evolution in FER systems achieving new successes using enhanced CNN architectures, transfer learning, and using hybrid implementations to improve accurate images.

MATERIALS AND METHODS

Deep learning

Deep learning systems require large amounts of data to produce accurate results, therefore enormous data sets are fed into them. By collecting and analyzing enormous amounts of data, Deep Learning creates a variety of predictive models to identify patterns and trends in the data. Because deep learning can automatically learn features from datasets and generate precise predictions based on the provided dataset, it is employed in multi-class classification applications. To increase the accuracy of image classification[21].

CNN

In this architecture, data will be analyzed by adopting multiple levels of datasets. Convolutional Neural Network (CNN) may contain these layers, such as convolutional layers, pooling layers, and fully connected layers. Convolutional layers are the first layer of CNN which is used to extract features from images. The next layer is ReLU also known as the activation function. ReLU stands for rectified linear layer. The pooling layer is the third layer of CNN. It plays an important role in image pre-processing techniques. The pooling layer is a technique of slightly decreasing the size of the image that was generated in the previous layer (ReLU). Pooling layers decrease the size of feature maps, supporting essential data while decreasing the amount of computation needed. The last layer is fully connected, also called a dense layer [31]. These layers are shown in Figure 1.

CNN Architecture

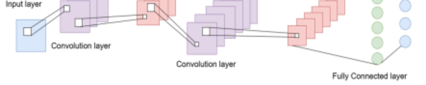

Figure 1. Architecture of Convolution Neural Networks Model

Table 1: Models and Layers of CNN Architecture

Models	**Total Layers**	**Convolutional Layers**	**Fully Connected Layer**	**Characteristics**
AlexNet	8	5	3	ReLU, Max Pooling, Dropout
ImageNet	-	-	-	-
resnet18	18	17	1	Residual Blocks (2-layer)
resnet50	50	49	1	Bottleneck Residual Blocks
				(3-layer)
resnet101	101	100	1	Deeper Bottleneck Blocks
Vgg16	16	13	3	Small 3x3 Filters, Simplicity
vgg19	19	16	3	Small 3x3 Filters, Simplicity
Xception	71	71	-	Depth wise Separable
				Convolutions
inceptionV3	48	48	-	Inception Modules,
				Factorized Convolutions
Squeenzene	18	18	-	Fire Modules, Efficient
t				Architecture
desnet201	201	201	-	Dense Connectivity, Feature
				Reuse
mobilenetv2	53	53	-	Depth wise Separable
				Convolutions, Inverted
				Residuals
inceptionres	164	164	-	Inception Modules, Residual
netv2				Connections
Shuffle net	50	50	-	Pointwise Group
				Convolution, Channel Shuffle
nasnetlarge	403	403	-	Optimized by Neural
				Architecture Search for High
				Accuracy

Transfer Learning

Transfer learning enhances the efficiency and adaptability of a related dataset by utilizing pre trained models from an individual ML task. The pre-trained model improves the efficiency of large datasets and reduces the duration of training. Transfer learning techniques used for deep learning and NLP (natural language processing). E.g. pre-trained models (AlexNet, Image Net, Res Net Squeeze Net) are used for medical images, classification, and analysis of emotions. Transfer learning not only improves the efficiency of large datasets but also improves the ability of pre-trained model results. It enables the use of advanced models for certain tasks without needing a large amount of data relevant to that area. Transfer learning has appeared as a vital approach in AI, easing the quick development and implementation of models in diverse sectors such as healthcare, finance, autonomous driving, and language translation. Transfer learning's ongoing progress has the potential to greatly enhance its applications and efficacy, confirming its position as a fundamental aspect of contemporary artificial intelligence advancement.

Proposed Methodology

In this session, we have to discuss our proposed methodology. In this proposed method we are modifying the version of the AlexNet CNN design for the achievement of tasks, e.g., image classification and feature detection. The change primarily targets the fully connected layers, namely (fc6, fc7, fc8), which are merged and adjusted to enhance performance. Our method consists of first training the original AlexNet model on three benchmark datasets (FER 2013, CK+, JAFEE) and then including the enhanced fully connected layers. The altered architecture is further refined through the implementation of a particular dataset to assess its efficacy. The performance of the modified AlexNet will be evaluated in comparison to the benchmark model to highlight the improvements made during these modifications.

1) AlexNet

AlexNet improved the domain of image processing by exhibiting the effectiveness of deep convolutional neural networks (CNNs) in image classifying tasks. AlexNet's architecture consists of eight layers. The layers are shown in Table 2.

Table 2: Layers of AlexNet Architecture

Name	Input-Size	Filters	Filters Size	Stride	Padding	Output-size	Neurons
Input	277*277*3	/	/	/	/	/	/
CONV1	/	96	11*11	4	0	55*55*96	/
POOL1	/	/	/	2	/	27*27*96	/
CONV2	/	256	5*5	1	2	27*27*256	/
POOL1	/	/	/	2	/	13*13*256	/

CON V3	/	384	3*3	1	1	13*13*384	/
CON V4	/	384	3*3	1	1	13*13*384	/
CON V5	/	256	3*3	1	1	13*13*256	/
POOL 3	/	/	3*3	2	/	6*6*256	/
FC6	6*6*256=9216	/	/	/	/	/	4096
FC7	/	/	/	/	/	/	4096
FC8	/	/	/	/	/	/	1000

Proposed Methodology Architecture

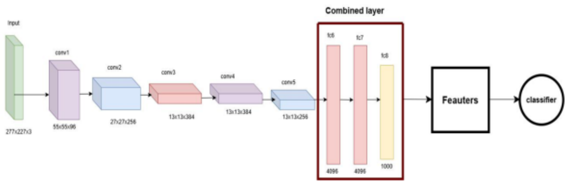

Figure 2. Proposed Methodology of Alexnet with Classifier in Combined Layer

In our proposed Methodology, we have modified the deep learning AlexNet model using different classifiers in combined layers (fc6, fc7, fc8). Classifiers are used in SVM (quadratic, cubic), Ensemble, and Neural Networks (wide, medium). First, the pre-trained AlexNet is employed for feature identification, by using deep convolutional and pooling layers. The features from the fc6, fc7, and fc8 layers are extracted and merged into a single unified feature vector through concatenation, preserving the unique characteristics of each layer. This merged feature vector is normalized to ensure consistency and improve classifier efficiency. The unified features are then fed into various classifiers, including Support Vector Machines (SVM) with quadratic and cubic kernels, ensemble methods, and neural networks with wide and medium architectures. Each classifier is trained and validated on the merged features to identify the most effective approach. The model's performance is evaluated using metrics like accuracy, precision, and recall, and the results are compared against the standard AlexNet to demonstrate the effectiveness of the proposed modifications.

RESULTS

Experimental Setup

Table 3: Experimental Setup for the Analysis of Facial Expression for the Detection of Emotional &Psychological Disorders

Datasets	CK+, FER-2013, JAFEE
Tool	MATLAB
Version	R2023b
Processor	Intel(R) Corei5-7200U CPU @2.60GHz
Ram	16GB

Hardware accelerator	CPU
Image type	PNG, JPEG
Learning rate	0.0001

Dataset

In this study, three benchmark datasets are FER-2013, Cohn Kahn (CK+), and Japanese Female Facial Expression (JAFEE). Details are given in this session.

2) Dataset FER-2013

The FER-2013 dataset is a popular benchmark. Grayscale images of facial expressions consist of seven manually annotated emotion labels angry, disgusted, fearful, happy, sad, surprised, and neutral. The key features of this dataset are shown in Table 4.

Table 4 : key features of FER-2013 datasets

Key Features	**Details**
Image Size	48*48 pixels
Total Images	35887 Images
Training Image	28709 Images
Testing Images	3589 Images

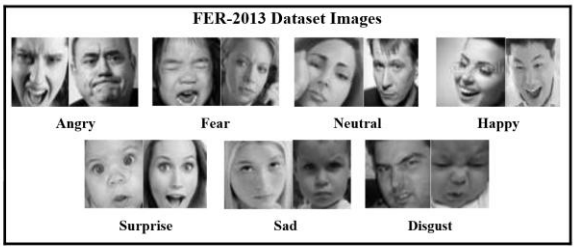

Figure 3: Seven facial expressions of the FER-2013 dataset

3) Cohn Kahn (CK+) dataset

Facial expression analysis uses the CK+ dataset as a notable benchmark. Enhanced classification and more annotated sequences are features that make it a modification of the original Cohn-Kanade dataset. The key features of this dataset are shown in the Table 5.

Table 5: key features of CK+ datasets

Key Features	**Details**
Image Size	48*48 pixels
Total Images	981Images
Training Image	688Images
Testing Images	293Images

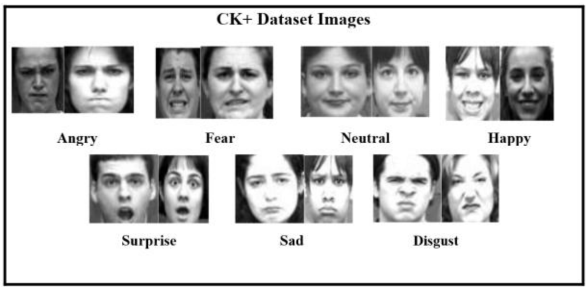

Figure 4: Seven facial expressions of CK+ Dataset

4) Japanese Female Facial Expression (JAFEE) dataset

The Psychology Department of Kyushu University set up a popular FE database known as the JAFFE dataset. There are seven different facial expressions represented in the 213 images, which include 10 Japanese female models. These expressions include happiness, sadness, surprise, rage, disgust, fear, and neutrality. Every image is 256 * 256 pixels in resolution and is grayscale. The dataset is useful for research in facial expression recognition, affective computing, and emotion analysis since it is annotated with both the expression labels and the subjective judgments of each expression. These are shown in Figure 5.

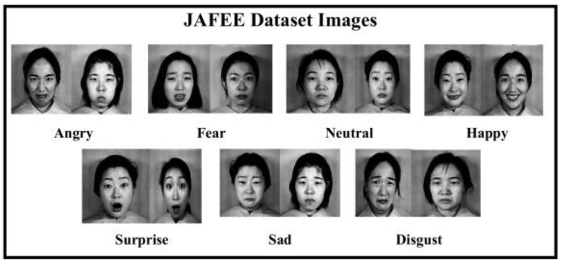

Figure 5: Seven facial expressions JAFEE Datasets

Results of Transfer

5) CK+ dataset Results

The effectiveness of transfer learning is proved by evaluating different pre-trained models while using the CK+ dataset. The total image of this dataset is 981 images split into 70% training and 30% testing data across seven classes. With an accuracy of 75.77%, DenseNet201 outperformed the other models by a wide margin. ResNet101 came in second with 69.28% accuracy, followed by ResNet18 and MobileNetV2 with 65.19% and 64.51%, respectively. With an accuracy of 49.83%, AlexNet, the starting point model, performed the worst, highlighting the significant gains made possible by transfer learning. Models with accuracies below 30%, such as VGG19, Xception, and InceptionV3, performed less well. With DenseNet201 demonstrating the greatest promise for this unique dataset, our results highlight the importance of transfer learning in improving model performance on tasks. These results are shown in Table 5 and Figure 6.

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Table 5: Results of CK+ dataset using CNN model on transfer learning

CK+ Dataset

Total Images = 981 images	
Training Data = 70%	
Testing Data = 30%	
Classes = Seven	
Model Name	**Accuracy**
AlexNet	49.83%
ImageNet	62.12%
resnet18	64.51%
resnet50	57.00%
resnet101	69.28%
Vgg16	59.39%
vgg19	20.48%
Xception	28.33%
inceptionV3	25.94%
Squeenzenet	43.34%
desnet201	75.77%
mobilenetv2	65.19%
inceptionresnetv2	28.33%
Shuffle Net	29.69%
Nasnetlarge	54.27%

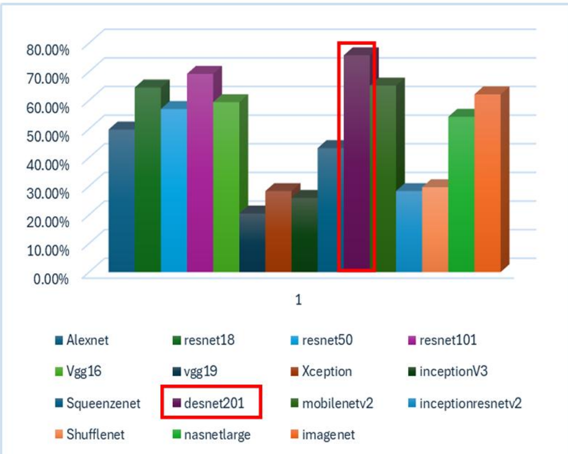

Figure 6: Results of the CK+ dataset using CNN models on transfer learning to highlight the highest accuracy.

6) FER-2013 Dataset Results

The effectiveness of transfer learning is proved by evaluating different pre-trained models on the FER-2013 dataset. The total images of the FER-2013 dataset are 35887 images split into 70% training and 30% testing data for seven different emotion classes. With an accuracy rate of 26.37%, Squeeze Net outperformed MobileNetV2 (24.97%). With a 23.74% accuracy, DenseNet201 likewise showed impressive performance. Conventional models with accuracies of 17.63% and 18.40%, respectively, were proved by AlexNet and ResNet101. Other models with accuracies ranging from 13.77% to 17.58%, like VGG16, VGG19, and Xception, also fared badly. Although transfer learning improves model performance in general, these results show that for the FER-2013 dataset, some designs perform better than others. Squeeze Net and MobileNetV2 stand out as being more efficient options for this situation. These results are shown in Table 6 and Figure 7.

Table 6: Results of the FER-2013 dataset using the CNN model on transfer learning

FER-2013 Dataset

Total Images = 35887images
Training Data = 70%
Testing Data = 30%
Classes = Seven

Model Name	**Accuracy**
AlexNet	18.40%
ImageNet	19.18%
resnet18	21.87%
resnet50	19.26%
resnet101	17.63%
Vgg16	13.77%
vgg19	14.55%
Xception	17.58%
inceptionV3	16.56%
Squeeze net	26.37%
desnet201	23.74%
mobilenetv2	24.97%
inceptionresnetv2	21.66%
Shuffle Net	20.24%
Nasnetlarge	14.95%

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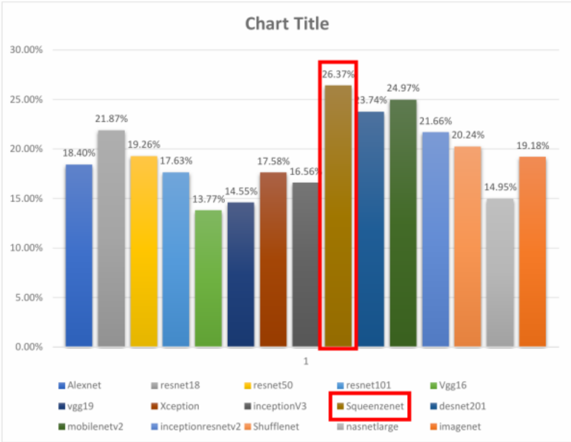


Figure 7: Results of the FER-2013 Dataset using CNN models on transfer learning to highlight the highest accuracy.

7) JAFEE Dataset Results

The effectiveness of transfer learning is proved by evaluating different pre-trained models on the JAFEE dataset which has 213 images divided into 70% training and 30% testing data for seven different emotion classes showing notable differences in performance. Out of all the models examined, DenseNet201 performed the best, with a maximum accuracy of 71.88%. ResNet50 and Shuffle Net both did well, with 67.19% and 65.62% accuracy, respectively. More moderate findings, ranging from 32.81% to 39.06%, were displayed by several models, including ResNet18, MobileNetV2, and Xception. Models with accuracies ranging from 14.06% to 18.75%, on the other hand, included AlexNet, VGG16, and VGG19. These findings show how well-suited some architectures are for using transfer learning to enhance model performance for the JAFEE dataset, especially DenseNet201, and ResNet50. These results are shown in Table 7 and Figure 8.

Table 7: Result of JAFEE dataset using CNN models on transfer learning

JAFEE Dataset

Total Images = 213 images
Training Data = 70%
Testing Data = 30%
Classes = Seven

Model Name	**Accuracy**
AlexNet	18.75%
ImageNet	23.44%
resnet18	39.06%
resnet50	67.19%
resnet101	34.38%
Vgg16	15.62%
vgg19	14.06%
Xception	25.00%
inceptionV3	17.19%

Squeenzenet	25.00%
desnet201	71.88%
mobilenetv2	32.81%
inceptionresnetv2	20.31%
Shuffle Net	65.62%
Nasnetlarge	26.56%

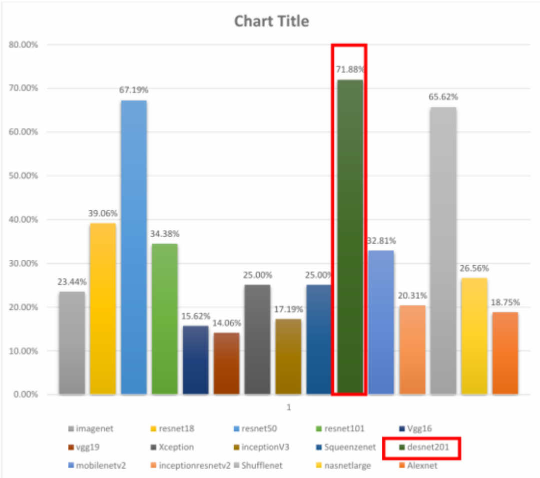
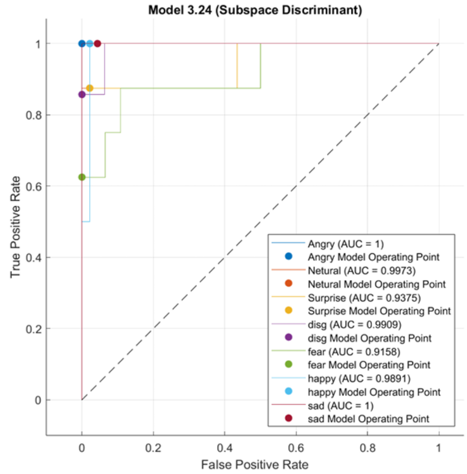


Figure 8: The graph shows the result of the JAFEE Dataset using CNN models on transfer learning to highlight the highest accuracy

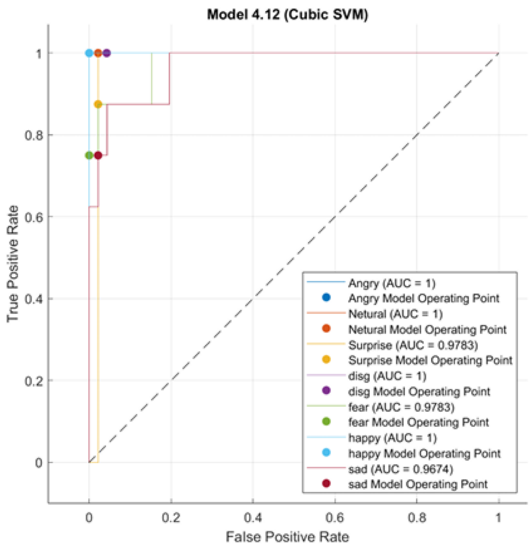
Result of Proposed Methodology

In this section, the proposed method AlexNet modification in combined layer (fc6, fc7, fc8) using different classifiers to improve the performance of deep learning techniques. SVM (quadratic, cubic) and Ensemble classifiers obtain high accuracy on the CK+ dataset while the training and accuracy rate is 90.70%, SVM (cubic) and Neural Network (wide, medium) classifiers obtain high accuracy on the FER-2013 dataset while training and accuracy rate is 90.70%, 92.60%, and 88.90% respectively. The FER-2013 dataset performs well on Neural network (medium) classifiers 23.44% 39.06% 67.19% 34.38% 15.62%14.06% 25.00% 17.19% 25.00% 71.88% 32.81% 20.31% 65.62% 26.56% 18.75% 0.00% 10.00% 20.00% 30.00% 40.00% 50.00% 60.00% 70.00% 80.00% 1 Chart Title imagenet resnet18 resnet50 resnet101 Vgg16 vgg19 Xception inceptionV3 Squeenzenet desnet201 mobilenetv2 inceptionresnetv2 Shufflenet nasnetlarge Alexnet the accuracy rate is 92.60%. SVM (quadratic, cubic) and Ensemble classifiers obtain high accuracy on the JAFEE dataset while the training and accuracy rate is 90.70%. Ensemble and SVM (quadratic, cubic) classifiers produce an accuracy of 90.7% on JAFEE and CK+ datasets. The Neural Network (wide) classifier produces an accuracy of 90.7% and the Neural Network (medium) classifier produces a high accuracy of 92.6% on FER-2013 datasets. These results highlight the excellent performance of the proposed method for the better adjustment of different classifiers on the AlexNet Model. These results are shown in Table 8, Table 9, and Table 10.

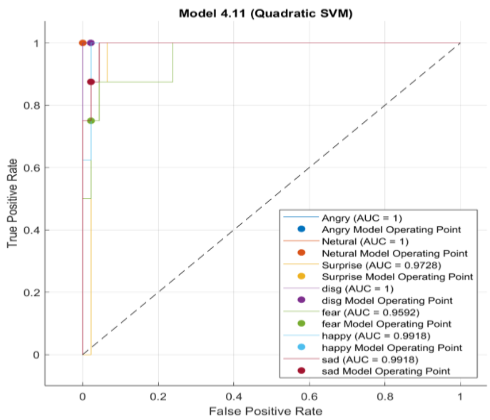
Figure 9: Graph of Proposed methodology using SVM (quadratic, cubic) and Ensemble classifiers on CK+ dataset



(a)

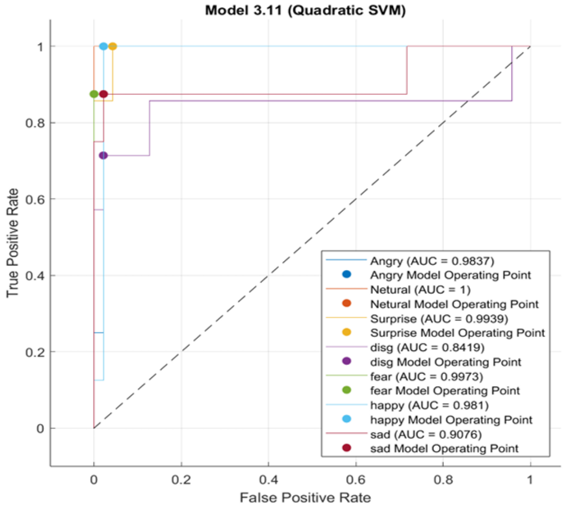


(b)

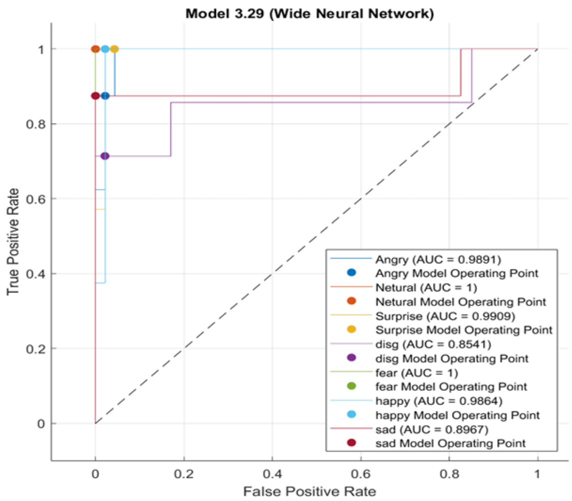


(c)

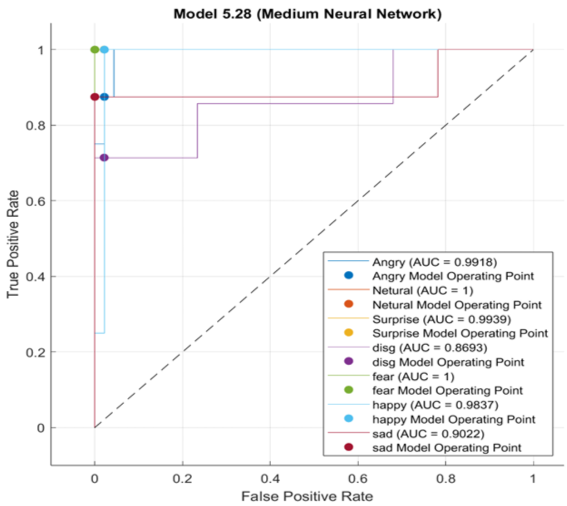
Figure 10: Graph of Proposed methodology using Neural Network (wide, medium) and SVM (cubic) classifiers on the FER-2013 dataset



(a)

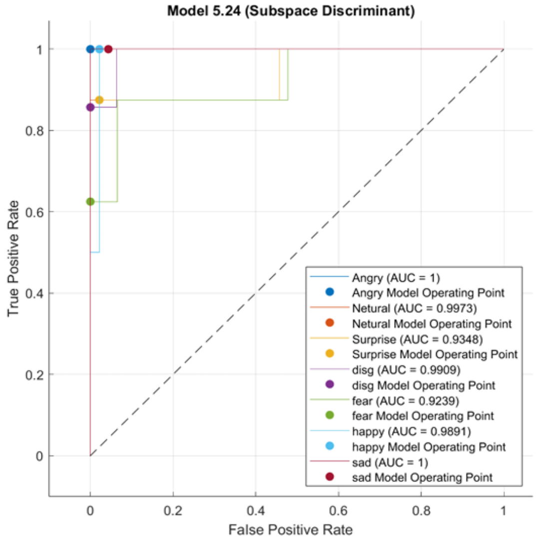


(b)

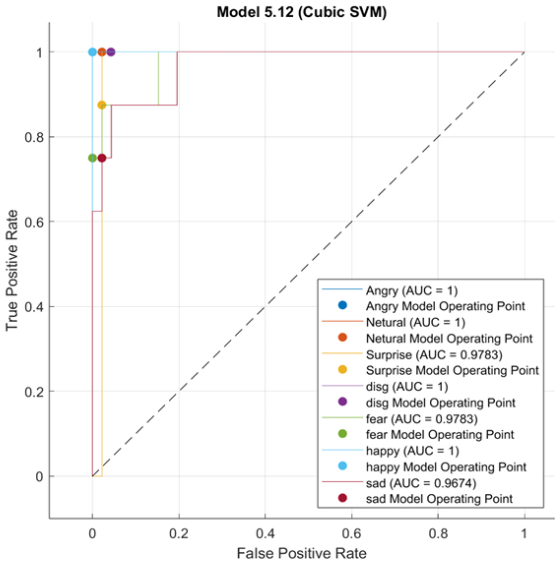


(c)

Figure 11: Graph of Proposed methodology using SVM (quadratic, cubic) and Ensemble classifiers on the JAFEE dataset



(a)



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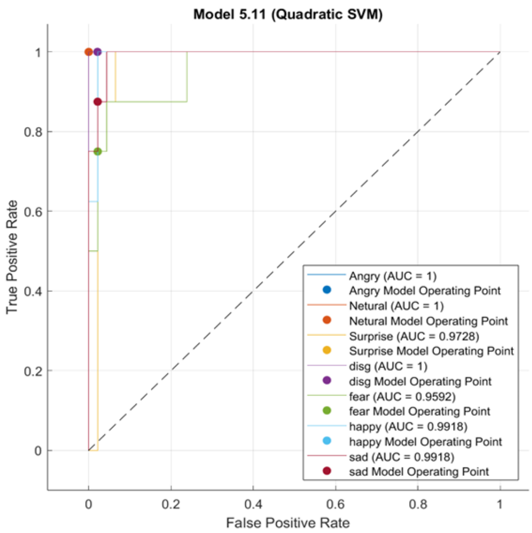

(c)

Table 8 : Results of the Proposed Methodology using different classifiers on the AlexNet Model

Dataset	CNN	Layer	Classifier	Accuracy
Jaffee	AlexNet	combined (fc6, fc7, fc8)	SVM (quadratic)	90.70%
Jaffee	AlexNet	combined (fc6, fc7, fc8)	SVM(Cubic)	90.70%
Jaffee	AlexNet	combined (fc6, fc7, fc8)	Ensemble	90.70%
FER-2013	AlexNet	combined (fc6, fc7, fc8)	neural network(wide)	90.70%
FER-2013	**AlexNet**	**combined (fc6, fc7, fc8)**	**neural network(medium)**	**92.60%**
FER-2013	AlexNet	combined (fc6, fc7, fc8)	SVM(Cubic)	88.90%
CK+	AlexNet	combined (fc6, fc7, fc8)	SVM (quadratic)	90.70%
CK+	AlexNet	combined (fc6, fc7, fc8)	SVM(Cubic)	90.70%
CK+	AlexNet	combined (fc6, fc7, fc8)	Ensemble	90.70%

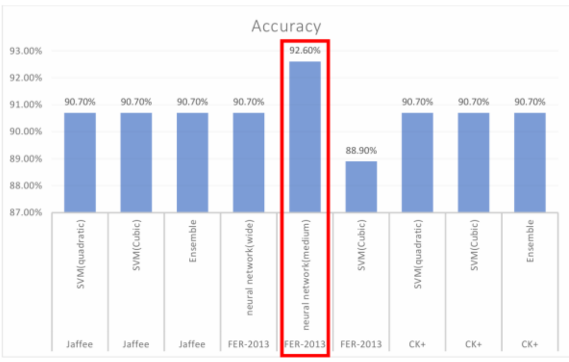

Figure 12: Results of modifying the AlexNet model to highlight the highest accuracy

Discussion

In this section, Traditional transfer learning methods and proposed method results are compared with each other. CK+ dataset performed well in DesNet201and the accuracy rate is

75.77% on traditional transfer learning models. On the other hand, the proposed method (AlexNet modified) is well performed in SVM (quadratic, cubic), and Ensemble the accuracy rate is 90.7%. JAFEE dataset performed well in DesNet201and the accuracy rate is 71.88% on traditional transfer learning models. On the other hand, the proposed method (AlexNet modified) is well performed in SVM (quadratic, cubic), and Ensemble the accuracy rate is 90.7%. The FER-2013 dataset performed well in Squeeze Net and the accuracy rate is 26.37% on traditional transfer learning models. On the other hand, the proposed method (AlexNet modified) is well performed in neural networks (medium) and the accuracy rate is 92.6%. In this comparison, the proposed method (AlexNet modified) shows better results as compared to traditional transfer learning methods(Bukhari et al. 2022; Das and Neelima 2023; Shangguan et al. 2023). The comparison results are shown in Figure 13, and Figure 14.

Comparison Result	
Transfer Learning (traditional model)	**Proposed Methodology (AlexNet) layer (fc6, fc7, fc8)**
CK+ Dataset	
• **DenseNet201= 75.77%** • ResNet101= 69.28% • ResNet50= 67.19%	**SVM (Quadratic, Cubic), Ensemble** = 90.70%
FER-2013 Dataset	
• **Squeeze Net= 26.37%** • MobileNetV2=24.97% • DenseNet201=23.74%	• Neural Network (Wide)= 90.70% • **Neural Network (Medium)= 92.60%** • SVM (Cubic)= 88.90%
JAFEE Dataset	
• **DenseNet201= 71.88%** • ResNet50= 67.19%	**SVM (Quadratic, Cubic), Ensemble** = 90.70%
• Shuffle Net=65.62%	

Figure 13: Comparison between transfer learning (traditional models) and modifying the AlexNet model

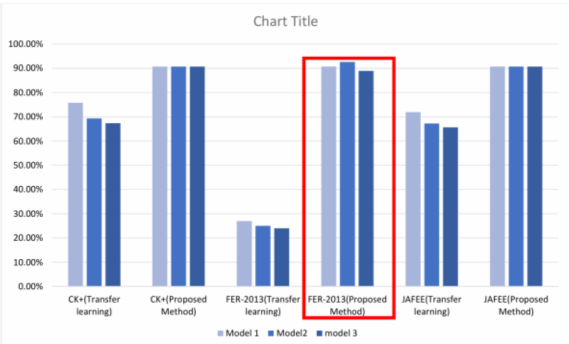

Figure 14: Results between transfer learning (traditional models) and modifying AlexNet model to highlight the highest accuracy

Conclusion

Conclusion In this work, CNN pre-trained models trained in Transfer learning performed on three benchmark datasets FER-2013, CK+, and JAFEE from extraction of facial expression recognition. In our research, the proposed method performed well as compared to traditional transfer learning methods. Transfer learning was well performed on DesNet201 and ResNet. On the other hand, the proposed method of AlexNet modification used combined layers (fc6, fc7, fc8) and classifiers to improve accuracy. The ability of the proposed method to extract facial features and continuously perform to produce high accuracy. The specific modification of classifiers to improve the ability of deep learning models for the detections of emotions classification. Satisfactory result of our proposed method and they need more research and modifications of different areas.

Future Work

In this work, we have modified the deep learning AlexNet model using different classifiers on combined layers (fc6, fc7, fc8). In the future direction, we need to modify other layers of the AlexNet model using different classifiers. They need to experiment with different models of Deep learning like CNNs and RNNs on multiple data sources (images, audio, video, or text) to improve accuracy. They also need to deploy our model in real-time series like Mental health clinics.

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The guidelines for citing electronic information as offered here are in modified illustration of the adaptation by the International Standards Organization (ISO) documentation system and the American Psychological Association style (APA, https://apastyle.apa.org/).

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