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Gender Classification Based on Hybrid Deep Learning Algorithm

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Abstract: - Gender detection has become one of the major aspects in Computer Vision applications from security to personalize experience. Recently Deep Learning algorithm using CNN has made significant improvements in Face detection and gender identification. Even though the problems like pose variations, over fitting and miss predictions have been observed. To overcome this drawback hybrid approach of Convolution Neural Network (CNN) is proposed for gender detection using publically available datasets. The proposed deep learning concept uses a MTCNN and CNN-RF algorithm where extraction of features is conducted using CNN followed by RF Classifier enhances the model robustness. The model is trained and tested using three different datasets, CKPlus, KMU-FED, KDEF and TFEID. Pre-processing of the data is done by resizing, contrast stretching and grey level transformation of datasets which are previously sorted in Male and Female labels. Results of Hybrid architecture provided the comparative analysis of different performance parameters. It was found that the model shows nearly same accuracy of 92%. In future the work can be extended for custom dataset for Real-Time prediction of Gender and classify them.

Keywords: CNN, MTCNN, RF and Gender detection

I. INTRODUCTION

Due to wide applications in the domain of computer vision for face detection, gender identification has gained a wider scope as face is used for identification of human being [1]. Due to this different techniques are developed in facial emotion detection and gender identification. Many algorithms are developed in the field of face detection and gender identification. Algorithm such as HAAR cascade has gained a wider area in field of detection and classification of faces [2] [3]. Also multi fusion algorithms are used for gender identification [4] [5]. Also many machine learning architectures[6] and also ageNet, FaceNet, ResNet and GoogleNet architectures were developed for detection facial features and classify them[7][8][9]. Different deep learning approaches have gained a significant result in gender detection [10] [11]. Later on the Transfer learning approach and hybrid algorithms proved to be better in facial feature extraction and detection [12] [13]. Attention based models are also used for gender classification [14]. Proposed hybrid approach performed better on gender detection. The MT-CNN algorithm is used for Feature extraction and the hybrid model of CNN and RF algorithm is used for classifying. The proposed model was trained on four different datasets and performance was computed to obtain Accuracy, Precision, Error, Sensitivity, F1 Score and FPR.

II. LITERATURE REVIEW

Many researchers have proposed different models for improving the performance of gender detection. Few research articles are given below. Shan Sung Liewet. al. proposed a novel approached of optimized CNN architecture[15]. Architecture uses fused convolution and sampling Layers, and processing uses a cross correlation. Proposed model uses SUMS dataset with an accuracy of 98.75% and AT&T datasets with an accuracy of 99.38%. MingxingDuan et. al. proposed a CNN-ELM (Extreme Learning Machine) architecture. The model underwent tests for gender and age. For training MORPH-II and Adience datasets are used. The accuracy obtained for proposed model was found to be 88.2% for gender detection [16]. Ozkan et. al. used a modified CNN model for detection of gender. The model was compared with other machine learning algorithms and it was found that model accuracy was 88.54% when trained with Adience dataset [17]. Tiagrajah V. Janahiraman and colleagues presented a deep learning model using pre-trained models like VGG16, ResNet-50 and MobileNet. Asian Images from Google were collected for training the model from which 500 were male and 500 female faces. ImageNet models shows accuracy as VGG-16 88%, ResNet 85% and MobileNet 49%. The images were trained with 50 epochs [18]. Md. Mahbubul Islam et. al. proposed a model based on Pareto

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frontier Convolution Neural Network with pre trained ImageNet models like GoogleNet, SqueezeNet and ResNet50. The accuracy obtained was more than 90% for all models. [19] Mohammed KamelBenkaddour proposed a CNN for age and gender detection. 99.10% accuracy was obtained from proposed model for Essex dataset and an accuracy of 95.6 % for Adience dataset [20]. Farhat Abbas et. al. used a model based on CNN model and Ant Colony Optimization. PKU-Reid dataset is used obtaining accuracy of 93% [21]. Pakizeet. al investigated a CNN-based model and Turkish Handwriting dataset. The model was trained on samples based on hand writing. Own dataset was constructed with 530 samples. It was found that mode shows an accuracy of about 74.46% [22]. Muhammad Usman Tariq et. al [23] proposed model based on two terms, one with histogram directed gradient and other with CNN. Two datasets were used FG-Net and UTK Face dataset. The most significant reduction was shown in the FG-NET dataset, where the mean absolute error decreased from 12.85 to 6.61. The model performed better than the others in terms of gender estimation on the majority of datasets. The error rate on the UTKFace dataset decreased from 20.45% to 10.6%. Our age mean absolute error was 5.66. SaeedAryanmehr et. al. proposed a model based on CNN for detection of gender using Iris. CVBL and UTIRIS were the two datasets used for testing the model. It was found that for two datasets the model accuracy is 90.32% and 96.25% [24]. J. Serinet. al. proposed a model based on CNN-SVM. SVM is used as a classifier in the model. It was noticed that with SOCOFing dataset the accuracy of recognition is obtained to be 99.25% [25].S.Bekhet et al. proposed algorithm for detection and validation of Gender from Single User image. An 82% accuracy rate for the model is found. Additionally, it was discovered that 74% of the time, a female is detected accurately, while 89% of the time, a male is. The model's efficiency for predicting gender is good, but it might still be further improved for predicting age [26]. SimanjuntakFrans et al. suggested using the VGGFace dataset to train a CNN model. The GENDER-FERET dataset was used to test the accuracy. It was discovered that the suggested fusion strategy of CNN and Crossfire filter enhanced the accuracy up to 98% and reduced the prediction error rate by up to 50%. Using the CNN features for gender prediction in conjunction with the Crossfire (Combination of Shifted Filter Responses) feature proved to be an additional benefit [27].

Table 1: literature Review

Author	**Algorithm**	**Dataset**	**Accuracy**
Shan Sung Liew et. al. [15]	Optimized CNN architecture	SUMS	98.75%
		AT&T	99.38%
MingxingDuan et. al. [16]	CNN-ELM	MORPHII	88.2% ± 1.7%
		Adience	
Ozkan et. al. [17]	Modified CNN	Adience	88.5%
Tiagrajah V. Janahiraman et. al. [18]	ImageNet models	VGG-16	88%
		ResNet-50	85%
		MobileNet	49%
Md. Mahbubul Islam et. al. [19]	Pareto frontier Convolutional Neural Network	GoogleNet	More than 90%
		SqueezeNet	
		ResNet50	
Mohammed KamelBenkaddour[20]	CNN model	Essex	99.10%
		Adience	95.6%
Farhat Abbas et. al. [21]	CNN model and Ant Colony Optimization	PKU-Reid	93%
Pakize et. al. [22]	CNN	Turkish handwriting	74.46%

Muhammad Usman Tariq et. al. [23]	Histogram of directed gradients CNN	FG-Net UTK Face	
SaeedAryanmeh r et. al. [24]	CNN model	CVBL	90.82%
		UTIRIS	96.25%
J. Serin et. al. [25]	CNN-SVM	SOCOFing	99.25%
S. Bakhet et. al. [26]	CNN	Custom Data set University of Palestine students' photos	Male-89% Female- 74%

The literature review shows that different algorithms were developed for gender detection. It was also found that the models were trained for different datasets. Different datasets such as UTK Faces, FG-Net, SUMS, AT&T, MORPH-II an many were used for different models. It was also seen that for gender recognition many models were trained for facial features. Facial features are used for gender detection. Some researchers proposed model based on Iris technology, one of model was based on handwriting samples were trained using Turkish handwriting dataset and also AI model was trained for detection of gender. And also finger prints were used for detection of gender.

III. METHODOLOGY

For gender categorization, the hybrid CNN-RF model in this design incorporates MT-CNN. The suggested model's flow procedure is shown in Fig. 1.Process Flow shows the steps involved in gender detection. Data processing, Pre-processing which includes Image resizing, Debluring using Lucy-Richardson algorithm, Contrast Stretching, feature extraction using MTCNN and CNN-RF for classification.

Data collection

The process of obtaining the information required, such as text or pictures that need to be forecasted, is known as data collection. In this concept, gender is identified by the data collected from the images.

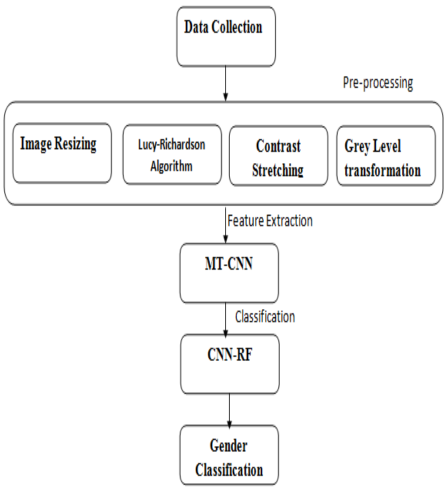


Figure 1: Work flow of proposed methodology

The Pre-processing:

Raw data from data gathering is not suitable for high-accuracy classification by a classifier. Consequently, particular pre-processing techniques are used to attain great precision.

Image Resizing:

Image scaling, which is used to increase and decrease the given image size in pixel format, is a crucial part of image processing techniques. This model is designed to resize both dataset images in the same order using the 256x256 pixel format.

Lucy-Richardson algorithm:

Non-blind deconvolution techniques use a point Spread Function (PSF) of an input image as a guide. It is an iterative method used for deconvolution. This algorithm is generally used for obtaining sharp image from blurred image using PSF.

Contrast Stretching:

Contrast stretching is a technique used for enhancement of Image. It is also known as normalizing that seeks to increase contrast by "stretching" the range of intensity values of an image by linearly mapping the image pixel intensity values.

Grey-scale transformation:

Grey level transformation is a technique used for image enhancement. The vertical axis of a histogram is determined by the pixel count in the image, while the horizontal axis spans from 0 to 255 in the grey level image.

Feature Extraction:

Feature extraction is a step where the raw data is processed and a meaningful data is extracted from raw data. Generally it is used to reduce the dimensionality of the raw data. MTCNN algorithm works by scaling resize the image to different dimensions based on the input, to every network layer, then sorting three independent networks based on their detection accuracy from poor to good utilizing the rough to fine principle. The multi-task detection aim is then achieved via a three-convolutional neural network cascade structure [18]. Facial detection, face boundary regression, and face point attribute positioning are all tasks that the MTCNN algorithm can do at the same time. Since the three tasks require different training labels, they each need distinct loss functions.

Classifier:

The obtained data is divided into labelled class as male and female. Such division of classes in to labelled groups through an algorithm s called classifier. This model uses a hybrid CNN-RF model to identify gender (male and female).

While machine learning only focuses on classification, deep learning algorithms incorporate both feature extraction and classification. Therefore, distinct feature extraction approaches are required for machine learning to categorize. In this approach, the RF is used for classifying and the CNN is used for extracting features. This is achieved by switching the CNN's fully linked layer to RF for classification. Consequently, the hybrid CNN-RF model is created when CNN and RF are combined.

IV. Results

The Data collection is the first process for gender classification using different datasets. The collected dataset is pre-processed for adjusting the size, deconvolution using Lucy-Richardson algorithm and enhanced using contrast stretching. After pre-processing the facial organs are localized and segmented using the MTCNN algorithm. These segmented features are then given to CNN-RF classifier which is used for classification of images into two labels as male and female. The collected output of random sample inputs of different datasets are evaluated and compared for performance analysis.

Data collection

Four different datasets are used and processed for performance evaluation. These datasets are classified and labelled as male and female categories. The classifier is trained using these four different labled datasets and results are obtained. Different datasets are mentioned below.

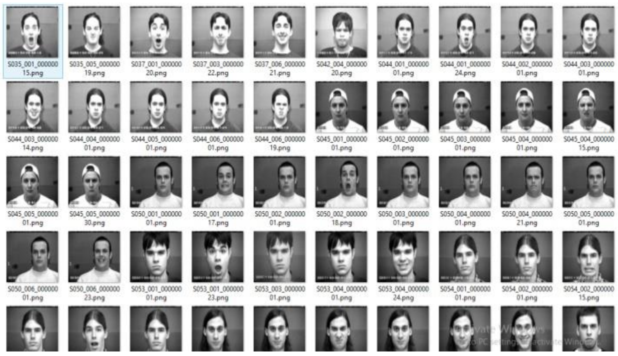


Figure 2: Male Faces in CK Plus Dataset

Figure 3: Female Faces in CK Plus Dataset

CK Plus dataset comprises of 593 video sequences, recorded at 30 fps. Fig 2 and Fig 3 shows the separation of faces as Male and Female respectively with the labels 0 and 1.

Figure 4: Male Faces in TFEID Dataset

Figure 5: Female Faces in TFEID Dataset

Fig 4 and Fig 5 shows the Male and Female faces for TFIED dataset. TFIED dataset is The Tokyo Face Image Expression data set which uses 40 to 50 male and female subjects.

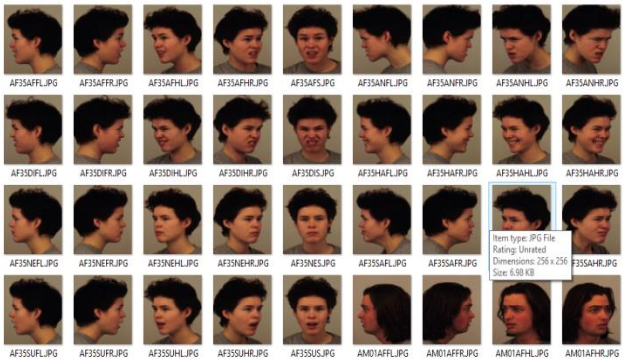


Figure 6: Female Faces in KDEF Dataset

Figure 7: Female Faces in KDEF Dataset

KDEF (Karolinska Directed Emotional Faces) is a dataset of 70 individual subjects from which 35 are male and 35 are female. Fig 6 and Fig 7 shows the images from KDEF dataset which are high quality static images. Images are classified for 6 different emotions, and are labelled as male and female for gender detection.

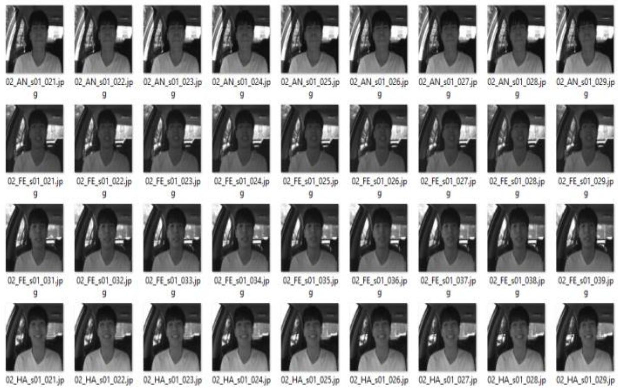


Figure 8: Male Faces in KMU-FED Dataset

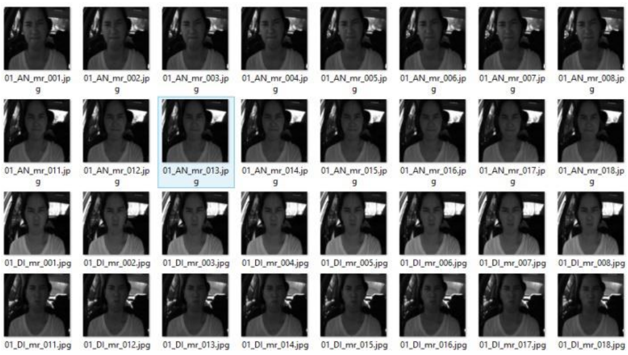
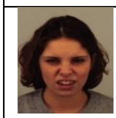
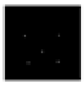
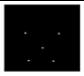


Figure 9: Female Faces in KMU-FED

Keimyung University Facial Expression of Drivers (KMU-FED) dataset is shown in fig 8 and Fig 9. KMU-FED dataset consists of posed and spontaneous images for more than 100 subjects.

Pre-processing Result

Table 1: literature Review

Original image	Image resizing	Lucy-Richardson	Contrast stretching	MTCNN
CKPLUS dataset				
				
TFEID dataset				
				
KDEF dataset				
				
KMU-FED				
				

Pre-processing table shows the image processing on input sample image. The result provides shows the image after resizing, after applying Lucy- Richardson algorithm and after Contrast stretching. Also The MTCNN is plotted for two sample images.

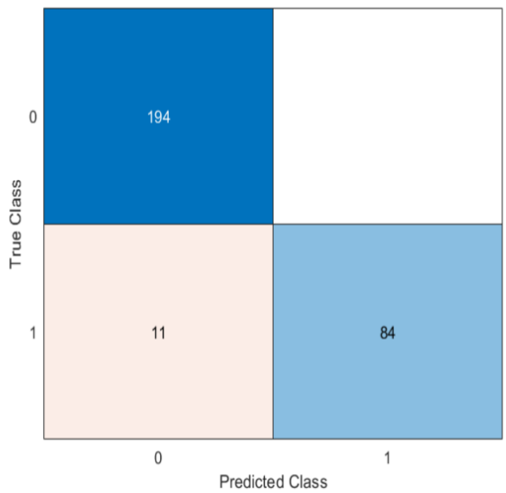


Figure 10: Confusion Matrix(CK Plus)

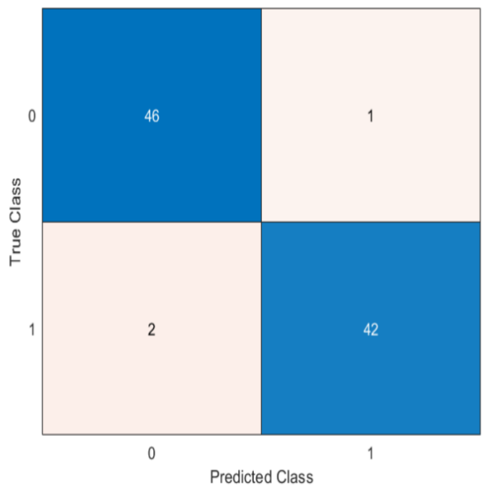
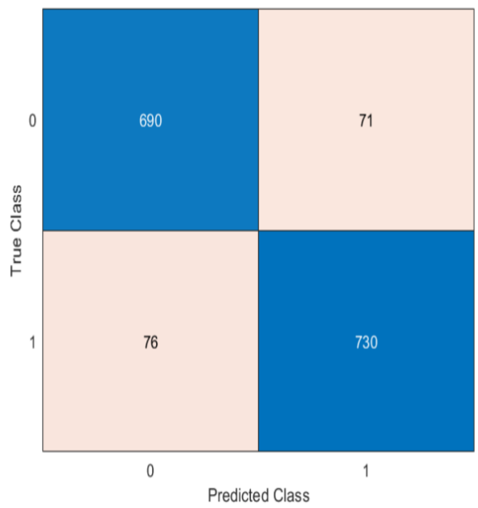


Figure 11: Confusion Matrix(TFEID)



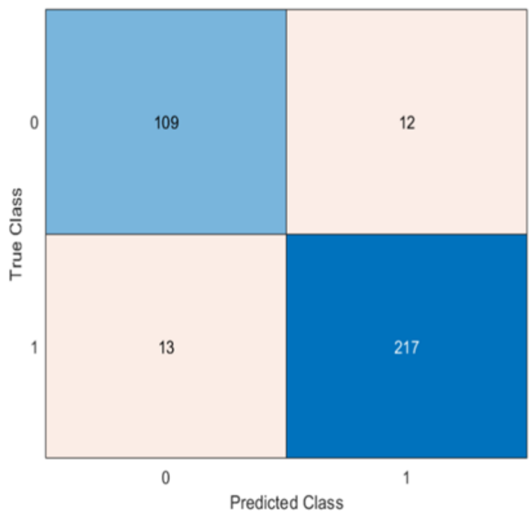
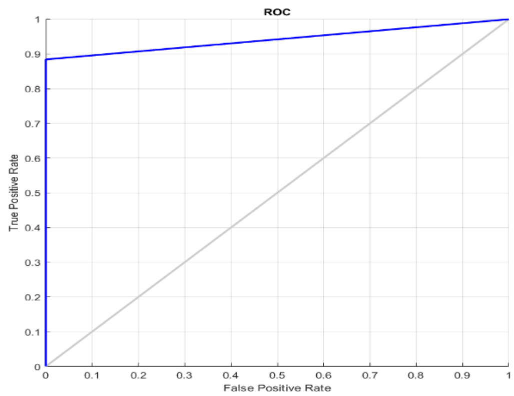


Figure 12: Confusion Matrix (KDEF)

Figure 13: Confusion Matrix(KMU-FED)

Figure 10, 11, 12 and 13 represents the confusion matrix of CKPlus, TFEID, KDEF and KMU-FED dataset. The confusion matrix of four different datasets shows the comparisons of actual class and predicted classes. 0 and 1 class is chosen for determining male and female.



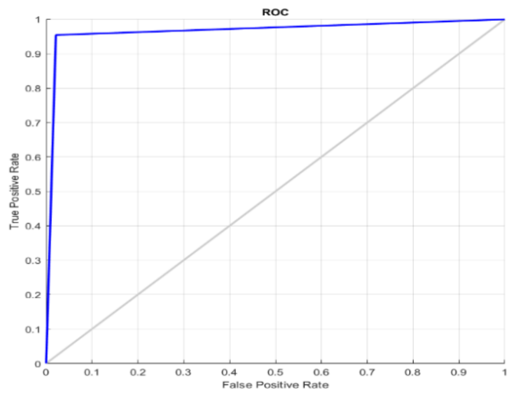
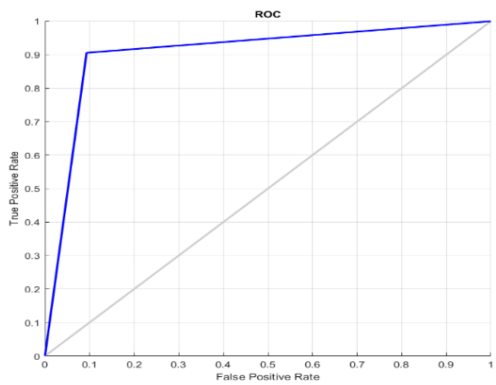


Figure 14: ROC for CKPlus

Figure 15: ROC for TFEID



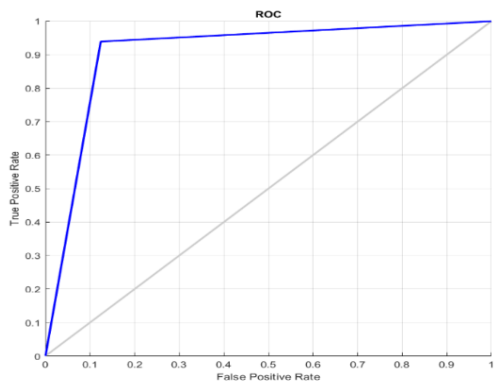


Figure 16: ROC for KDEF

Figure 17: ROC for KMU-FED

Figure 14, 15, 16 and 17 represents a graph of ROC for different datasets. Receiver operating Curve (ROC) plots TPR and FPR at different thresholds. It is observed that if the threshold is lowered the classification of mode items is possible which results the true and false positives.

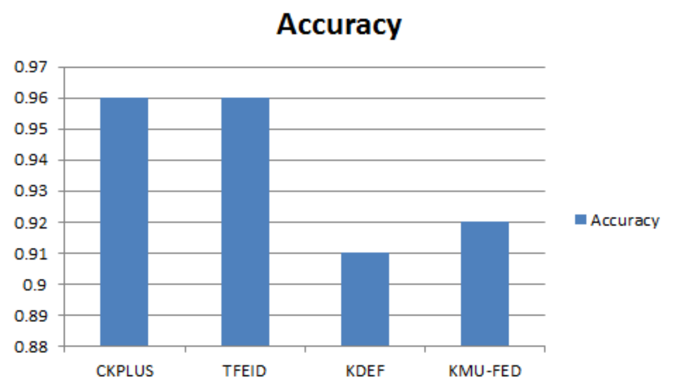


Figure 18: Comparison of Accuracy

Accuracy for different datasets is compared in Fig 18. It was seen that the proposed model works better on CK plus and TFEID with a accuracy of 96% where as for KDEF and KMU-FED it is 91% and 92 % respectively.

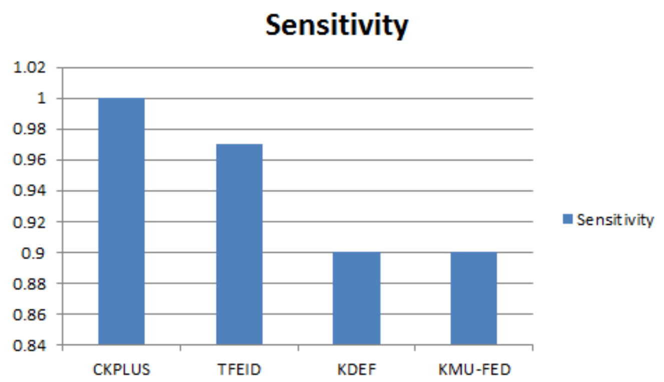


Figure 19: Comparison of Sensitivity

Fig 19 shows that the sensitivity for CK plus is 1 which determines that, all positive instances are detected correctly.

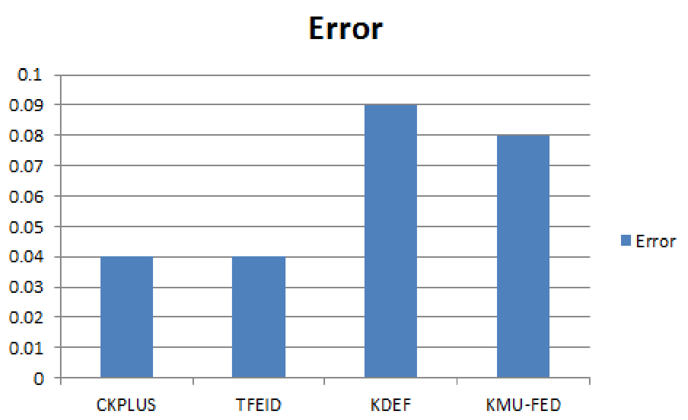


Fig 20: Comparison of Error

Fig 20 shows the graph of error rate. Error rate for CK plus, TFEID is less with value0.04.

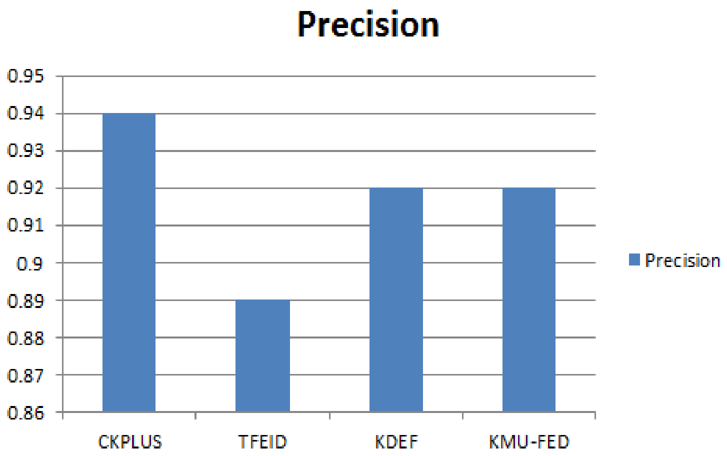


Figure 21: Comparison of Precision

Fig 21 shows graph of precision. Precision of model provides information of the instances predicted by model as positive is actually positive.

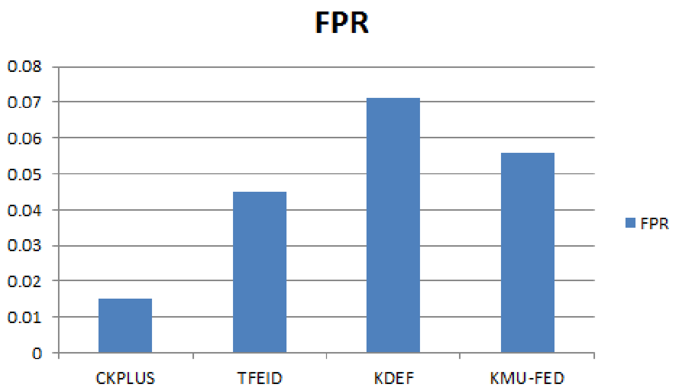


Figure 22: Comparison of FPR

FPR denotes that model prediction as true positive values as false positive values. FPR for four datasets is shown in Fig 22.

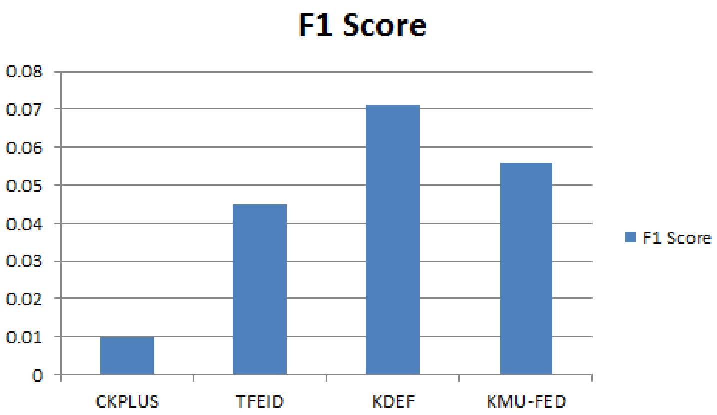


Fig 23: Comparison of F1 Score

F1 Score is given in Fig 23 for four different datasets. F1 Score obtained for different datasets is as CK Plus 0.01, TFIED 0.045, KDEF 0.071 and KMU-FED 0.056.

Table 3: Comparative analysis for different datasets

Parameters	CKPLUS	TFEID	KDEF	KMU-FED
Accuracy	0.96	0.96	0.91	0.92
Sensitivity	1	0.97	0.90	0.90
Error	0.04	0.04	0.09	0.08
Precision	0.94	0.89	0.92	0.92
FPR	0.015	0.045	0.071	0.056
F1 Score	0.01	0.045	0.071	0.056

Table 3 shows the comparison of parameters for two different datasets for proposed model.

V. CONCLUSION AND FUTURE WORK

Gender detection model is proposed using MTCNN and CNN-RF algorithm. Three datasets are been compared and tested using the proposed model. Result of different parameters was compared for different datasets. The proposed model demonstrates strong performance across multiple datasets, achieving the highest accuracy of 96% on CK Plus and TFEID, followed by 91% on KDEF and 92% on KMU-FED. Notably, the model shows perfect sensitivity 1 for CK Plus, indicating it correctly identifies all positive instances. The error rate for CK Plus and TFEID is low, at 0.04, further highlighting the model's robustness. Precision values indicate that the model reliably predicts positive instances, with CK Plus achieving the highest precision at 0.94, and other datasets like KDEF and KMU-FED showing similarly strong precision scores of 0.92. The FPR (False Positive Rate) is minimal, suggesting that the model rarely misclassifies positive instances as false positives. The F1 Score, which balances precision and recall, is consistent across datasets, reflecting a solid performance in maintaining a balance between detecting true positives and minimizing false positives. Overall, the model exhibits promising results across diverse datasets, demonstrating its effectiveness for emotion recognition tasks.

In future the model can be tested for costume dataset and can be extended for real time applications. Using different algorithms along with CNN can also give better results. Use of Transfer Learning, Modified CNN model will provide better result.

Conflicts of Interest

“The authors declare that they have no conflicts of interest.”

Author Contributions

Frameworking, Sarvajeet Bhosale and Dr.Sangeeta R. Chougule; Procedure, Sarvajeet Bhosale; software, Sarvajeet Bhosale; validation, Sangeeta R. Chougule; formal analysis, Sangeeta R. Chougule; investigation, Sangeeta R. Chougule; resources, Sarvajeet Bhosale; data curation, Sarvajeet Bhosale; Preparation of the initial draft, Sarvajeet Bhosale; Changes and assessments, Sarvajeet Bhosale; visual representation, Sarvajeet Bhosale.

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