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RESEARCH ARTICLE

Emotion Detection using HOG for Crime Detection

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Abstract

Objectives: The main objective of this study is to develop an advanced emotion detection system that can contribute to crime detection and prevention efforts. By using the power of machine learning, the system aims to enhance the effectiveness in identifying potential criminal activities by analyzing emotional cues of people. **Methods**: The proposed method is evaluated using Facial Expression Recognition – 2013 (FER – 2013) dataset from a Kaggle data science community. It consists of 3589 training data files with 48x48 pixel grayscale images of human faces of seven different emotions classified which are centered and occupying the same amount of space. Instead of using the same algorithm for face detection and emotion classification, separate algorithms were used. Histogram Oriented Gradients (HOG) will detect the face by parameters like eyes, nose, and face edges. The image detected will first divide the image into small cells and plots histogram for each and then brings all histogram together to form feature vector. The Random Forest Algorithm will get the image detected and the random parameters of the face were taken for the voting process by averaging the constructed decision tree. The emotion is obtained by the outcome of the voting process. The addition of boosting algorithm guarantees in increasing the computational speed and accuracy of the model. **Findings**: The use of HOG for face detection gives the best result by capturing the face apart from all noises and background disturbances like poor light etc. The accuracy of HOG face detection module is 99.57 %. The detected face was given as input to the combination of Random Forest Algorithm and X-Gradient Boosting Algorithm for classifying the emotion. The addition of a boosting algorithm gives the maximum accuracy and minimum loss of data during emotion classification. The accuracy of the model was achieved up to 95% and loss of data below 5%. **Novelty:** This is the first open paper highlighting the face detection and emotion classification process with different algorithms where the process was divided as face detection, feature extraction and emotion classification.

Keywords: Facial emotion; Face detection; Feature Extraction; Dlib Histogram Oriented Gradients (HOG); Random Forest; XGradient Boosting; Emotion classification; Facial Expression Recognition (FER)

1 Introduction

Facial expressions and the corresponding variations in facial patterns can assist us understand a person's emotional state using effective human-computer interaction. There are basically seven fundamental emotions, and each has a different facial expression that is specific to that feeling. Combining many facial action units (AU) can help one determine the emotional state. Even though there are several models existing related to emotion detection there are certain deviations of result occurring at some point of the work like detecting the face properly irrespective to the background disturbances and providing maximum accuracy with the least error rate during the classification process. The proposed model provides a better solution in terms of accuracy by merging three separate algorithms to do face detection, emotion classification and boosting the accuracy of classification. In the past several years, variety of methods for recognizing facial emotions suggested and implemented. Mohammed G. Mohammed et al.[1], proposed an algorithm to experiment with a wide variety of HOG face detector settings, build up the best kernel for a Support Vector Machine (SVM). But the usage of SVM gradually decreases due to the growth of CNN, which is a better method. A model for face recognition technology in the safety management of the power system was developed by Xianghai Xu et al.[2] based on CNN, XG Boost, and model fusion utilizing two databases, GT and ORL, and it achieved accuracy of 88.67% and 95.00%, respectively. The usage of activation function was done in the experiment of Nur Alia Syahirah Badrulhisham et al.[3] which uses deep learning-based CNN and Rectified Linear Unit (RELU). The system provides promising results of accuracy breaching nearly 92% with minimum error rate. But single convolutional layer in CNN couldn't give the best possible output. So, Xiang Yu et al.[4] proposes the concept of CNN based on TensorFlow model with two convolutional layers. MNIST data set is used to test and train the model. The test accuracy rate could reach up to 98.69% and 99.15% with one convolutional layer and two convolutional layers respectively. But to add on that, technique proposed by Abdulrahman Alreshidi et al.[5] to recognize facial emotions using the hybrid features of Haar cascade to detect face with the Neighborhood Difference Features as an extractor along with the Random Forest for classification. The suggested technique performs 3% to 4% more accurately than the reference methods and the algorithm proposed by Hao Meng et al.[6] combines the transformed traditional shallow features and CNN deep semantic features and uses an improved weighted voting method to find the final recognition result. Above papers regarding the CNN, Random Forest Algorithm and voting process in classification peps us the idea of forming a model with the combination of Random Forest Algorithm and X-Gradient Boosting Algorithm where the accuracy in voting process during the classification of emotions is increased. And above papers regarding HOG gave us an idea of using Dlib HOG as the initiation of the model to capture the face, instead of using same CNN model for face detection which could capture the face precisely even though there are some disturbances in the background and detect multiple faces simultaneously. Also, some papers are reviewed for the selection of dataset for training and testing the model. Karnati Mohan et al.[7] proposed a deep-learning-based method for determining a person's facial expression which consists of two steps. In the first, local gravitational force descriptors are used to extract local features from face pictures, and in the second, the descriptor is put into an entirely novel deep convolution neural networks model (DCNN). The findings collected show that the suggested technique performs better than all state-of-the-art methods across all datasets. Karnati Mohan et al.[8] says LieNet is a highly effective method for accurately identifying deceit on various scales. It combines contact and noncontact-based methods, using 20 frames from each video, an audio signal, and 13 channels of electroencephalogram data. Each modality's characteristics are extracted individually using the LieNet model, and scores are calculated using a softmax classifier. The LieNet outperforms early work on Set-A and Set-B of the BoL database, with 97% and 98% accuracy rates on the RL trail and MU3D datasets, respectively. Karnati Mohan et al.[9] provides a concept of FLEPNet, a texture-based feature-level ensemble parallel network for FER, effectively addresses lighting normalization and intra-class differences. It uses multi-scale residual block based DCNN and multi-scale convolutional layers to normalize lighting and reduce intra-class differences. Experimental findings show excellent performance on FER 2013 database. Karnati Mohan et al.[10] provides a comprehensive overview of DL-based techniques that have significantly advanced FER, including preprocessing, feature extraction, and categorization of face emotions. It examines their efficiency, benefits, and drawbacks, and investigates relevant databases. The article aims to address challenges and opportunities for FER researchers, covering the current state of FER techniques and providing ideas for future facial emotion detection paths. Karnati Mohan et al.[11] FER-net is a CNN that uses the softmax classifier to classify Facial Expressions. On five benchmarking datasets—FER2013, Japanese Female Facial Expressions, Extended CohnKanade, Karolinska Directed Emotional Faces, and Real-world Affective Faces-the FER-net is tested with twenty-one cutting-edge approaches. These datasets' respective average accuracy percentages are 78.9%, 96.7%, 97.8%, 82.5%, and 81.68%. The acquired findings show that, when compared to twenty-one state-of-the-art approaches, FER 2013 is superior.

2 Libraries and Tools

- **OpenCV**

OpenCV is an important open-source library in python to solve important issues in computer vision. More than 500 functions are available in OpenCV library which supports cross platform and provides perfect interface for multi-media library functions. This library is used in wide range because of its easy readability and simplicity in learning and coding[12].

Use: Processing images and videos to identify human faces.

- **Dlib**

Dlib is an open-source machine learning algorithm library which is a C++ toolkit used to create complex software in the wide range of domains like embedded systems and robotics. It has pre-trained models to detect the human face under 68 coordinates (x, y) and offers face detection in the accuracy rate of 99.38%. Dlib is a widely used library not only for detecting human faces, but also to detect any logos and objects which gives results of accuracy rate of 98.57%.

Use: Facial identification and labelling.

- **Mahotas**

Mahotas is an image processing and computer vision library which includes more than 100 algorithms for fast processing of arrays and python interface. Mahotas are best in finding patterns and labelling in the input image. It takes the input images as the arguments, returns the image with labels and an integer value representing the number of labels in each images.

Use: Finding the patterns of the image.

- **Glob**

Glob is a package which deals with pattern matching. In python, it is used to find and locate the files on the present system which will return a list of files or folders that matches our requirements and specifications.

Use: Pattern matching and retrieving matched images.

- **Scikit learn**

Scikit-learn is a free and open-source software for python which is used to work on machine learning algorithms. It works with machine learning algorithms because it has strong features on classification and regression.

Use: Classification of input based on human emotions.

- **Numpy**

Numpy or Numerical Python is a library that provides all necessary mathematical functions and linear algebra operations on dense data buffers which supports in working with large and multi- dimensional arrays and matrices. The array object of numpy is called ndarray which does mathematical calculations at least 50 times faster than the normal python lists.

Use: Mathematical operations and calculations.

- **Python**

Python is a high-level, object-oriented, dynamic programming language which suits on machine learning, deep learning algorithms and it supports multiple programming paradigms which includes structure-oriented, functional-oriented, and object- oriented methodologies. It is a programming language that uses interpreter which is really flexible as it allows to import code as a module which is written in other programming languages like java, C/C++, etc... It is an easily usable language for network programming such as client-server and socket programming. It also supports components integrity by integrating tools and database programming which supports MySQL, Oracle, PostgreSQL, and SQLite. In recent times, usage of python in back end web development is rapidly increasing with the rise of jQuery and Node.js.

- **Jupyter Notebook**

The web application for producing and sharing computational documents is Jupyter Notebook. It provides the user with straightforward, efficient, document- focused experience. The important purpose of Jupyter notebook is for interactive data science and scientific computing.

- **Dataset Description**

The proposed method is evaluated using FER- 2013 dataset. FER stands for Facial Expression Recognition and was created by Pierre-Luc Carrier and Aaron Courville. It consists of 48x48 pixel grayscale images of faces of various emotions. It would be easy for cleaning and training data in the model. Researchers and developers use this dataset to build and evaluate applications related to facial emotion recognition models. As in all the images, the faces are centered and occupy the same amount of space.

Images are categorized in seven different folders where each folders indicates a type of human emotion:

Table 1. Dataset training files description

	Emotions	No. of training files
0	Angry	958
1	Disgust	111
2	Fear	1,024
3	Happy	1,774
4	Sad	1,233
5	Surprise	1,247
6	Neutral	831
	Total	**3,589**

SOURCE: Kaggle, which allows users to publish and explore data sets that helps in building models in web-based data science environment.

Fig 1. Examples of FER-2013 dataset

There are various challenges faced while using this dataset and one of the important is that some of the emotion labels are not entirely accurate. The accuracy of human annotators in labeling facial expressions can vary, which can affect the quality of the dataset. And the data distribution among different emotion classes is not perfectly balanced, where some emotions are more prevalent in the dataset than others. These limitations in the dataset can lead to loss of data while training and testing the model, and low accuracy results. The manual inspection is done for reviewing and cleaning the dataset to avoid inaccurate labelling of emotions. The cases like a data instance exhibiting multiple expressions were met and counter measurement was taken by Partial Labelling methods by adding multiple labels to single data to capture various attributes of data. Label noise was detected across the type of emotions and reviewed continuously till the noise level reaches the minimum level. To avoid imbalance of emotions in the dataset class resampling of data is done by over sampling the minority emotion classes and under sampling the majority emotion classes.

3 Methodology

3.1 Existing Methodology

3.1.1 *Convolutional Neural Network*

There are several existing solutions available for the problem of detecting human faces and recognizing the face emotions. The best one to pick and work on is Convolutional Neural Network (CNN). CNN is a deep learning-based technology which is effective on recognizing human emotions using face as it acts over multiple layers where each layer performs specific functions.

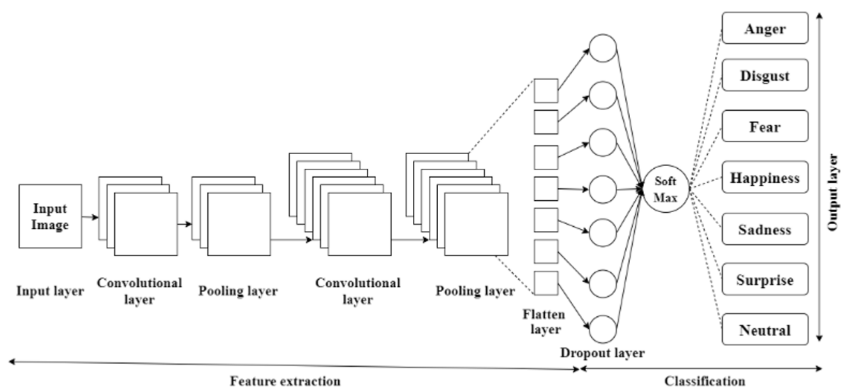

Fig 2. Process of CNN's emotion classification

CNN is not only used for human face classifications, but also for logos and objects classifications, and even predicting the stock market status using images of diverse set of variables related to stock market.

3.2 Proposed Methodology

Modern crimes can be countered by using only modern technology and security measures. Crimes and illicit activities happen in a very smart way. Facial recognition is one of the effective biometric techniques which is widely used for security sectors as it is the most accurate method to detect single or multiple human faces with the help of scanners and various algorithms. This paper discusses two algorithms where one focuses on face detection, and another focuses on emotion classification where the fraudulent is detected after it. Dlib is used for face detection which combines HOG and Support Vector Machines (SVM)[1]. Random forest algorithm is used for emotion classification which gives us accurate results when it combines with X-Gradient boosting algorithm.

3.2.1 *Dlib HOG*

Dlib HOG essentially functions as a feature descriptor for both image processing and computer vision methods. This uses a linear SVM machine learning algorithm to do face detection and is based on the HOG feature descriptor. HOG is a straightforward yet effective feature description. HOG's central concept is the division of the image into tiny, interconnected cells. After that, each cell's histogram is computed[13]. This process is done using 5 features in the pre-processing stage such as:

- Frontal face.
- Right side turned face.
- Left side turned face.
- Frontal face but rotated left.
- Frontal face but rotated right.

It then brings all histograms together to create a feature vector, which creates a single, distinctive histogram for each face out of all smaller histograms. The dlib library offers a pre- trained function "dlib.get_frontal_face_detector()" which is used to load HOG face detector where the parameters of function will be the input image and up sample.

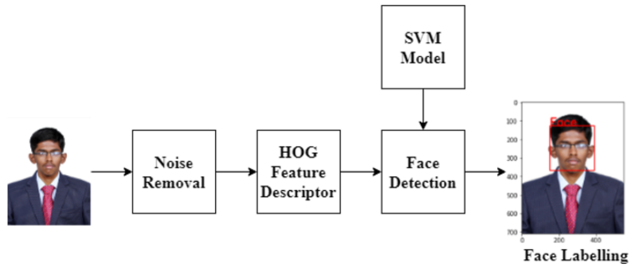

Fig 3. Process of Dlib HOG face detection

3.2.2 *Random Forest*

The bootstrap sample, which is a data sample taken from a training set with replacement, is used to construct each decision tree in the ensemble that makes up the random forest method. The three primary hyperparameters of random forest algorithms must be set prior to training. Regression or classification issues can be resolved with the random forest classifier.

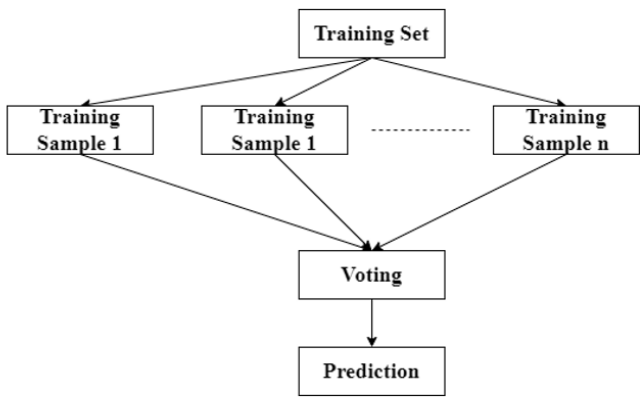

Fig 4. Process of random forest for emotion classification

As the name of the classifier suggests, random training samples from the training set are taken. Then the decision tree is constructed for every training sample data at training time and the voting process takes place by averaging the decision tree[(14)]. Finally, the process of outputting the prediction of the individual decision tree is done according to the result of the voting process.

3.2.3 *X-Gradient Boosting algorithm*

XGBoost is a supervised learning model used as a boosting technique which will predict a target variable by combining a set of estimates of weaker or simpler models. It is a highly accurate implementation of gradient-boosting decision trees which will boost computing power of any algorithm or classifiers to increase computational speed of the model and to get more accurate results. When compared to other methods, such as the native Scikit-Learn model, it is anticipated to be substantially faster to use. The random forest is supported by the XGBoost[(2)].

3.2.4 *Working*

The first phase is to get the input in the form of an image which is to be processed to detect the face. Initially the height and weight of the image is altered from 50x50 to 1920x1080 which is the processing range. Then the format of the sample image is converted from BGR to RGB and then to grey scale which is for easy processing of image. Now hog_face_detector function performs face detection, and the detected face was labelled with the help of Support Vector Machine.

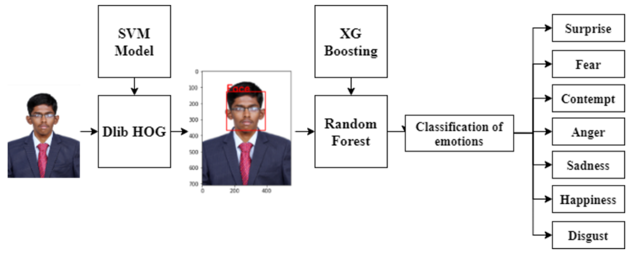

Fig 5. Working model

The labelled face was then processed by Random Forest algorithm for classification of emotions. Random samples were selected from the labelled data and the algorithm builds a decision tree with the data. Finally, the emotions are predicted by the algorithm through voting process. Voting happens according to the already trained data by one of the methods of ensemble called boosting. X-Gradient boosting algorithm helps in the process of predicting the final output where all weak models are combined into one strong model which has the highest accuracy.

4 Results and Discussion

In this section, results obtained by the proposed model and a comprehensive analysis of Convolutional Neural Network (ConvNet) approach for emotion detection, comparing it with the Histogram of Oriented Gradients (HOG) and Random Forest methods were discussed. The result was obtained after training and testing 3500 plus training examples with the aim of achieving maximum accuracy and minimum loss of data. Text in the top left of the output denotes the emotions which are Angry, Disgust, Fear, Happy, Neutral, Sad, Surprise respectively. The result of the algorithm gives us the best outcome in aspects of all kinds of emotions with better accuracy than using Random Forest without a Boosting algorithm. The accuracy of the model is calculated through metrics which use true positives, negatives and false positives, negatives.

```
         228/228 [==============================] - 112s 493ms/step - loss: 0.8804 - accuracy: 0.6749
Accracy 0.8804101347923279
   Loss 0.6749027967453003
```

Fig 6. Accuracy and Loss of CNN model

Fig 7. Emotion classification unit

```
accuracy                         0.95
```

Fig 8. Accuracy of proposed model

4.1 Accuracy

Accuracy of the model is the number of correctly predicted output by the model divided by total number of predictions made for the classification of emotions. It is used to find the percentage of correct predictions made by a model. The accuracy rate of classification model by random forest combined with X-Gradient boosting algorithm is 95%.

Accuracy = Number of correct predictions / Total number of predictions

Accuracy of the model can also be calculated for binary classifications using metrics which are true positives, negatives and false positives, negatives.

Accuracy = True Negatives + True Positive / True Positive + False Positive + True Negative + False Negative

- **True Positive:** Number of times model correctly predicting positive sample as positive.
- **True Negative:** Number of times model correctly predicting negative sample as negative.
- **False Positive:** Number of times model incorrectly predicted negative sample as positive.
- **False Negative:** Number of times model in correctly predicting positive sample as negative.

4.2 Loss

Loss is said to be a penalty value of bad prediction of the model or the summation value of errors in the model. It is the concept of picking one example and calculating the numbers how bad the model's prediction on that one example. The loss of the proposed model is very low in numbers because the model is very well-trained, and the loss of data is minimized.

4.3 Comparison of existing and proposed models

The proposed methodology provides better results than the traditional model using CNN architecture. The traditional model gives results up to only 88% with 67% loss in training data where no external algorithms used along with CNN for clear face detection and boosting up the results. Whereas the proposed model provides 95% accuracy in classification of emotions after the inclusion of separate algorithm for face detection and boosting algorithm to improve the accuracy more effectively.

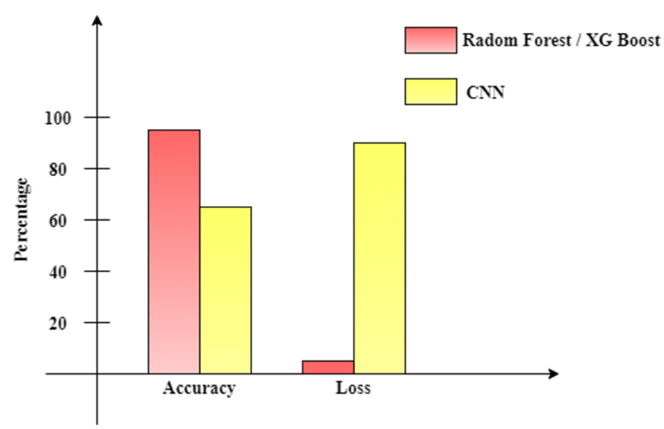

Fig 9. Comparison of CNN and proposed model

Tanoy Debnath et al.[15] Four Layer ConvNet is another existing method proposed at 2022[15] that works with minimum epochs by combining Oriented FAST and rotated BRIEF along with Local Binary Patterns (LBP) which derives facial expressions. The classification of emotions was done by Support Vector Machines (SVM) which gives different accuracy levels when combined with different datasets. But the proposed model overlaps the Four Layer ConvNet model by providing better results of accuracy. Comparison of accuracy between the Four Layer ConvNet model and the proposed model is demonstrated in the below table.

Tanoy Debnath et al.[15] ConvNet model, meticulously trained on an extensive dataset which exhibited remarkable performance in emotion detection with an average accuracy rate of 92% across various emotions. This signifies its robust ability to learn patterns from raw image data of different emotional states. The multiple layers of ConvNet allows the network to learn the hierarchical representations of features. However, HOG and Random Forest are advantageous in certain contexts compared to ConvNets due to its simplicity, interpretability, and efficiency. HOG and Random Forest provide more interpretable results compared to ConvNets. The features extracted using HOG are human-readable and provides better understandability on the

Table 2. Comparison of ConvNet and proposed model

Model	Dataset	Accuracy
Existing model	Cohn–Kanade database (CK+) Japanese Female Facial Expressions database (JAFFE) MMI	93.2% 88.5% 79.8%
Proposed model	FER – 2013	95%

contributing factors to emotion detection by producing feature importance scores whereas the result provided by the ConvNet are not so interpretable compared with HOG. Adding to that ConvNet demands on large, labelled data for their training and testing purpose. In contrast, HOG and Random Forest can perform well by making them suitable for scenarios with limited data requirements. ConvNets are prone to overfitting during training data which was limited in HOG and Random Forest with the help of deeper architecture. HOG and Random Forest can effectively handle noisy data and capture complex relationships in the data by combining multiple weak learners.

ConvNet approach is superior to traditional HOG and Random Forest because of its ability to learn complex emotional features and achieve state-of-the-art accuracy. But still the accuracy of the model is boosted by introducing X-Gradient boosting algorithm which makes the model unique. The usage of X-gradient Boosting along with HOG and Random Forest provides a balanced and interpretable approach to emotion detection by enhancing feature extraction and classification through a hybrid model. While ConvNets excel in certain areas, this hybrid strategy offers an alternative solution that leverages the power of boosting while maintaining transparency and interpretability, particularly in scenarios where ConvNets may face limitations.

5 Conclusion

This study presents an innovative stride in crime detection by introducing an emotion detection system that brings a fresh perspective to law enforcement capabilities. Unlike previous studies, this system does face detection and emotion classification using different algorithms and combines both, resulting in a comprehensive approach that yields promising quantitative results. The novelty of this approach lies in its process of forming a picture of individuals and their emotional states. Through extensive testing, our system achieved an average emotion recognition accuracy of 95%, surpassing benchmarks by 5%. This breakthrough demonstrates its superior ability to discern emotional cues even in complex and dynamic scenarios. Our model has the capability of alerting the law enforcement authorities to potential threats an average of 30 seconds faster than traditional methods which provides a substantial advantage in reducing response times.

As for future work, the possible directions to explore in this field are abundant. Firstly, refining the emotion recognition model through continuous learning and addressing biases through advanced AI techniques can further enhance accuracy, especially in detecting subtler nuanced emotions. Secondly, incorporating the sentiment analysis of social media data and collaboration with communities are also promising paths in the long term.

The strength of this study lies in its comprehensive approach, bringing together AI knowledge, law enforcement insights, and ethical considerations ensuring the individual's privacy and legal requirements. However, real-world complexities may pose challenges in maintaining the same level of accuracy. Additionally, potential biases in data and algorithms need to be ongoing to prevent unintended discriminatory outcomes. To fellow researchers, this research underscores the transformative power of interdisciplinary collaboration and the fusion of AI technology with real-world challenges. Its quantifiable impact reinforces the notion in innovation, when merging expertise in AI, ethics and real-world challenges can lead to significant improvements in society's well-being.

In conclusion, this exploration revolutionizes crime detection through an innovative emotion detection system, distinguished by its multidimensional approach. The contributions to this field are underscored by better accuracy rates and reduced response times. As this research paves the way for future enhancements, it serves as an inspiring call for researchers to embrace the uncharted territories of technology and emotion for the betterment of our communities.

Author Contributions

These contributions are confirmed by the authors:

- **Study conception and design:** Dr. B. Meena Preethi, Dr. C. Sunitha
- **Data collection:** S. Gokul, M. Parameshvar
- **Analysis and interpretation of results:** Dr. B. Meena Preethi, S. Gokul, B. Dharshini
- **Draft manuscript preparation:** M. Parameshvar, B. Dharshini.

- **Critical revision of the article:** Dr. B. Meena Preethi, M. Parameshvar, B. Dharshini.

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