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NEURAL NETWORK BASED EMOTION RECOGNITION THROUGH FACIAL EXPRESSION

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Abstract:

Emotions are states of mind that humans experience unintentionally and unconsciously, and they are accompanied by physical changes in the facial muscles that manifest as expressions. Facial emotion is frequently employed in human-computer interaction applications because it transmits the emotional states and sentiments of people via non-verbal communication techniques including facial expressions, eye movement, and gestures. Facial emotion identification is challenging since there is no universally accepted method for categorising facial expressions. Since the characteristics uutilised to represent the face in the machine learning algorithm are hand-engineered and reliant on past information, the algorithm will not attain a high accuracy rate when it comes to recognising emotions. In this study, a convolutional neural network (CNN) was trained to identify different expressions on people's faces. Nonverbal communication relies heavily on facial expressions, which reveal the speaker's true emotions. An abundance of studies have been conducted by many scholars on the topic of computer modelling of human emotion. Yet it's a long way from competing with the human eye. In this article, the Viola-Jones method has been used to identify the face's eye and lip regions, with the assistance of a neural network. Additionally utilised for this purpose are Machine Learning methods, Deep Learning models, and Neural Network algorithms. The authors of this research were able to deduce the subject's emotional state only by analysing the location of the lips and eyes. Anger, disdain, disgust, fear, pleasure, sorrow, and surprise are among emotions that will be discussed in this article as viable methods of detection. There are seven expressions that may be deduced from a frontal portrait of a human face.

Emotions, Feature Extraction, Viola-Jones, Neural Network, Emotion Recognition, Emotion Detection, Face Recognition are some of the terms used to describe these processes.

INTRODUCTION

Emotion recognition and interpretation rely heavily on ACIAL expressions. The word "interface" itself alludes to the significance of physical appearance in establishing rapport between people or things. The ability to read a person's facial expressions has been demonstrated in studies to have a profound

impact on how one understands what is being said and how a conversation develops. Almost ninety-three percent of the words said in any given discussion are affected by the speaker's or listener's emotional state, making emotional interpretation a crucial skill for every communicator. A human-computer interface (HCI) that can read human emotions would be ideal. For this reason, the focus of this study is on developing methods by which computers can accurately read the emotional states of their users via their different sensors. Human emotions were deciphered from facial expressions in this investigation. Several scholars have been drawn to the study of human emotions since Darwin's ground-breaking work in the field. As a species, we share a core set of seven emotions. A human's face may convey a wide range of emotions, from indifference to anger, contempt to fear, happiness to sadness, and surprise to surprise. This study suggests a reliable method for identifying four frontal facial emotions: neutral, happy, sad, and surprise. Emotion recognition techniques are maNy. In order to create system applications that are able to recognise emotions accurately, several techniques were proposed. By adapting their replies to the mood of their human users, computers might improve their communication. Emotions may be read from a person's words, his face, and even his gestures. This article reports research on automatic facial expression recognition. The standard method for identifying an individual's emotional state via their face is to analyse a face image that has been isolated from a background picture, and then identify facial segments or landmarks within the face regions. Following that, these face features are disentangled from various global and spatial landmarks. Last but not least, a classifier is trained to generate recognition results based on the isolated highlights; examples include the random forest classifier from the library. This is a deep learning application. In the realm of pattern recognition, deep learning is a tried-and-true paradigm. The Kera's package is used to build a Convolutional Neural Network (CNN) algorithm. To be more precise, a convolutional neural network (CNN) is a subset of the artificial neural networks that use a machine learning module. You can use a CNN to identify objects, recognise faces, analyse images, and do a lot more besides. Several layers of neural networks make to a deep convolutional neural network (DCNN). It may also be used to effectively mine data for useful insights. IJSER © 2020 http://www.ijser.org

Critical Analysis of the Literature

Many fields, including machine learning, natural language processing, neurology, etc., have made contributions to the study of identifying emotions in agiven situation. Before, they had each independently explored the potential of voice characteristics, textual data, and facial expressions as proxies for emotional state. There are a number of rigid categories that may be used to describe emotions, including joy, sorrow, disgust, wrath, fear, and surprise. Combining visual, aural, and written information has led to subsequent works being more effective. The combined information is as precise as possible. There are three distinct approaches to this fusion process: early, late, and hybrid. Emotional components and the interplay between emotional and rational processes are fundamental to other philosophies. Facial-Feature-Based Detection of Emotions A. This paper explores the use of machine learning and support vector machine for the purpose of recognising emotions (SVM). Image facial expression recognition, extraction, and assessment are possible thanks to the application of certain concepts. One such method is the use of object detectors, such as the Viola-Jones cascade, and key locations, such as the Harris corners, to isolate people's faces in photographs. The second is feature extraction using the histogram of oriented gradients (HOG). To characterise the seven most common human face emotions, a multi-class predictor was trained using support vector machines (SVM) (Anger, Contempt, Disgust, Fear, Happiness, Sadness, Surprise). the nose's stiff ridges. It has separate units for recognising faces and acting (AU). In several fields, including media and communication, content analysis and even law enforcement and healthcare, computers are now able to read facial expressions and determine a person's intent. Finally, one area where the real-time programme could use some tweaking is the user must maintain the same distance from the camera that was used to capture the neutral frame. If not, the reasoning behind the displacement ratios breaks down. It is possible to address this issue by rescaling the neutral distances in response to the user's motion.

Three Methods IJSER

It is recognised in this study that the training phase of machine learning presents the greatest difficulty. In cases when the algorithm has to learn from actual human responses to facial expressions. It's important for the first system to be familiar with the furious face, for instance, if the task at hand is to identify it. The first system must be familiar with the joyful face in order to recognise it as such. The re-training procedure has been used to teach the system to recognise certain emotions. The information used for re-training came from the actual world. The process of retraining was the most challenging aspect of this system. The system also includes a great deal of additional components. In order to analyse enormous datasets quickly and effectively, machine learning is a powerful tool. This makes it possible to recognise emotions with greater precision. It provides instantaneous responses. Nothing about the picture has to be kept in the system while it awaits some future outcome. Neoteric data mining methods, made possible by current computers, may examine thousands of data points in a relatively short period, saving a great deal of labour. In several fields, including media and communication, content analysis and even law enforcement and healthcare, computers are now able to read facial expressions and determine a person's intent. There are two primary methods of analysis described here: (Zhang's method and the Gabor wavelet coefficients). We will scale the retrieved faces to 100x100 pixels since Zhang has shown that this lower resolution (64x64) is sufficient. Compared to a Fisher's face, detection accuracy increases to 81% when just the HOG and SVM classifier are used. A single method. The dual-classifier technique achieves the same 81% accuracy as HOG, but it speeds up the testing procedure by 20%. Statistical Machine Verification Using Point Data (B) Sentiment Analysis in Real-Time In this study, a cascade of a multi-class SVM and a binary SVM are used to recognise emotional states using machine learning. Based on the mobility of 19 feature points, this method is designed to extract emotions. A person's lips, eyes, eyebrows, and nose are just a few of the many facial locations where feature points may be found. Predominantly, it is inflexible in its operation.

In order to gather as much information as possible, this is employed in both traditional and digital media throughout the data collecting phases. Pictures of friends, family, and even some random strangers showing a range of emotions are all part of the real world. They eliminated unnecessary data that had been saved for further examination. The information comes from a data collection on kaggle.com, which was compiled from various online media sources. This information collection was first made available on this website back in 2012. The site's emotional data collection is often considered to be the most reliable of its kind. The information was then transformed into facial portraits at a resolution of 48 by 48 grayscale pixels. Images and emotions are separated into their own areas. A number code from 0 to 6 is included in the section devoted to emotions. In addition, statements for each image include a string that may be found in the pixel portion. It's also important that the photo solely include a human face. A face image is a photograph of a face that has been reduced in size and cropped. And a distinct image.

Phase of training using deep learning

Convolutional neural networks are a wonderful example of how deep learning may be used for picture classification (CNN). When done using the python karas library, creating a CNN is a breeze. Pixels are the basic unit of visual representation in computers. Images often have neighbouring pixels. An image's edge, for instance, may be represented as a collection of pixels. This is used by convolutions for picture recognition. Perform a convolution, a pixel matrix is multiplied by a filter matrix, often known as a "kernel," and then the resulting values are added together. When that pixel is covered, the convolution moves on to the next one and continues doing the same thing. The diagram below illustrates this procedure.

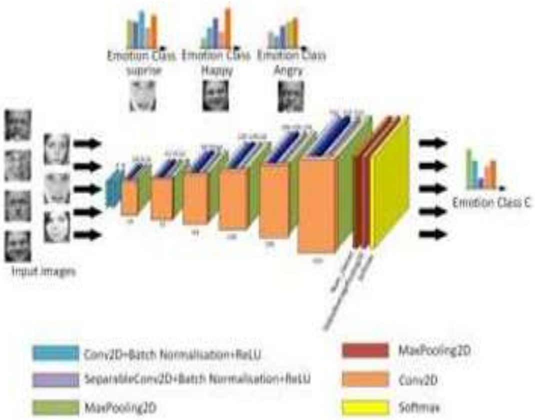

Figure: Emotion detection using Convolutional Neural Network

The Sequential model will be used here. Keres's easiest model-building approach is the sequential method. It might serve as a steppingstone as you develop your model. As a modelling method, we use the "add ()" method. Our methodology relies on the first two stages of Conv2D. Images are processed via convolution layers, which reduce them to 2-dimensional matrices for further processing. On the second layer, for instance, there are thirty-two fewer nodes than in the first. The size of the dataset will determine whether this sum has to be modified. For the time being, we will keep utilising both 64- and 32-bit sizes. The size of the convolution filter matrix we use is determined by the size of the kernel. When using a filter matrix of size 3, the kernel size must also be 3. If you forget what you were expected to remember, the first piece of text and the accompanying picture may serve as a reminder. In this context, "activation" refers to the layer's operational state. For our first two layers, we will use a rectified linear activation (REL) activation function. Empirical evidence demonstrates the activation function's efficacy in neural networks. The input layer of our network may likewise take shapes as inputs. Each input image has the format 28,28,1, where the 1 indicates grayscale, as was previously mentioned. A "Flatten" layer is located in-between the Conv2D layers and the dense layer. Convolution and thick layers are separated by the flatten operation. When the model has determined the most likely result, it makes a prediction. The next step is to compile the model. An optimizer, loss function, and input measurements are required by a model compiler. The optimizer determines how rapidly the system learns. Adam, a piece of software, will help them zero in on the best solution. Figure: An IJSER Convolutional Neural Network for Emotion Detection. The Sequential model will be used here. Keres's easiest model-building approach is the sequential method. It might serve as a steppingstone as you develop your model. As a modelling method, we use the "add ()" method. Our methodology relies on the first two stages of Conv2D. In specifically, convolution layers are responsible for Adam excels at optimising in many contexts. During training, the Adam optimizer may change the learning rate to maximise performance. How quickly the ideal model weights are found is a function of the learning rate. Whereas slowing the learning rate would raise the weights' correctness (at least somewhat), doing so would add a great deal of time to the computation process. Categorical cross-entropy is how we'll refer to the loss function we use. regarded as the peak of categorization. Scores closer to zero imply better model performance. During model training, the accuracy measure is used to verify the validity of the validation set. The 'fit ()' function will be fed the training data (train X), the target data (train y), the validation data, and the number of epochs in order to train the model. This dataset contains validation information drawn from the X test and y test subsets of the original test set. The epochs parameter controls how many times the model iterates through the data. We can improve the model somewhat by running additional epochs. No more progress can be made in the model from one epoch to the next after that point. Our model will include three distinct time periods. At reaching 93% accuracy for the validation set after 3 rounds, we may conclude that this method is quite promising.C. Detection: Two groups were determined using K-means clustering. A natural next step is to take the mean of the row containing the most information. We also get the absolute value by averaging the row with the lowest value. Concentrations of pixels with midrange values between the maximum and the lowest may be seen here. the number of picture segments is determined by the clustering result. The eyes are the first thing to be split using the bounding box function, and the number of components is what ultimately decides how many pieces there will be. Since they appear at the top of the image, the eyes are the first facial feature to be removed during a face separation. The ocular matrix is then sent into a distance-based algorithm that is used to identify and isolate distinct face features. After using K-means clustering to categorise the terms, the resultant picture was shown.

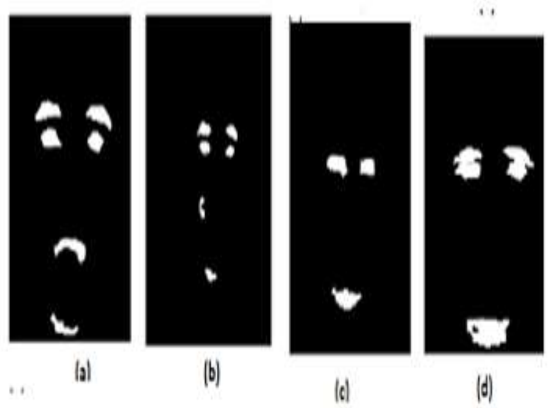

Figure: K-means clustering segmentation outputs

When trying to determine what an object is, the Viola-Jones method is often used. This algorithm's primary trait is the slow training time and the quick detection speed that it provides. The Haar basis is used in this method. The Haar characteristics areased in face detection. Examples of feature groups include:

i) Edge features

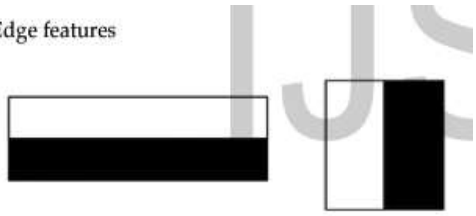

Figure: Edge features

ii) Line Features.

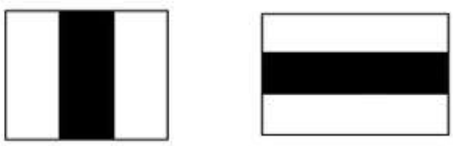

Figure: Line features

iii) Four Rectangle Features

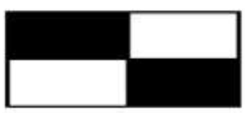

Figure: Four rectangle features

If we want to identify a person's face, for instance, we must first convert the picture to grayscale and then segment it.

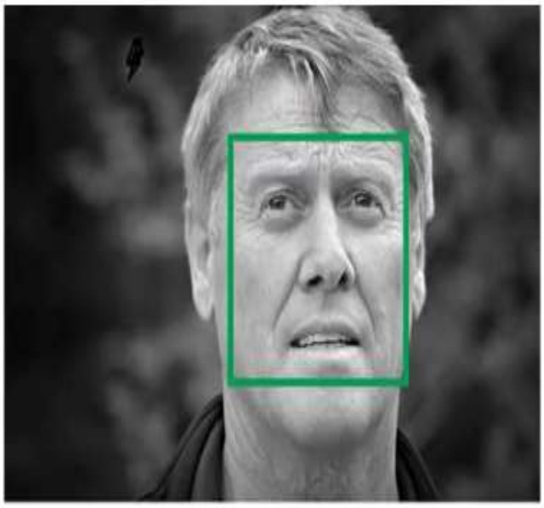

Figure: Landmark image

Well, let's assume we're into eyebrow recognition. Thus, edge properties are essential. Nose detection calls for the presence of black-white-black line features. Detection of teeth relies on edge features. When the Haar features are applied, the image is sent on to the next stage of processing. The comparison of these two features is the foundation of emotion recognition.

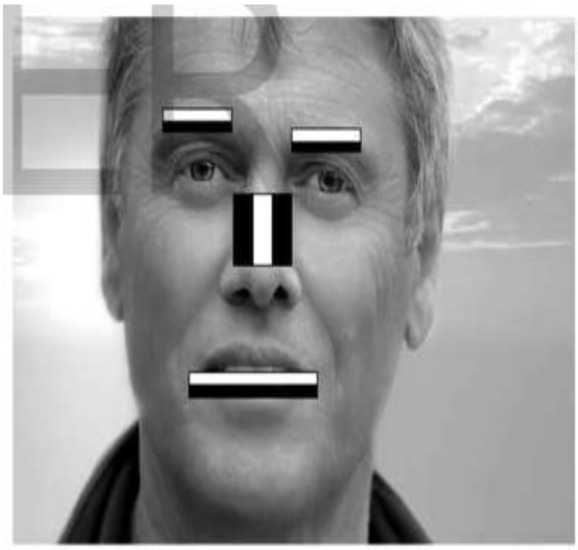

Figure: Haar features image

We can calculate value by using Fourier equation,

$$\Delta = dark - white = \frac{1}{n}\sum_{black}^{n} [(x) - \frac{1}{n}\sum_{white}^{n}](x)$$

The average value of the black area in a genuine picture is 0.74, whereas the average value of the white region is 0.18. Thus, the contrast between black and white in the actual picture is 0.56. (0.74-0.18).

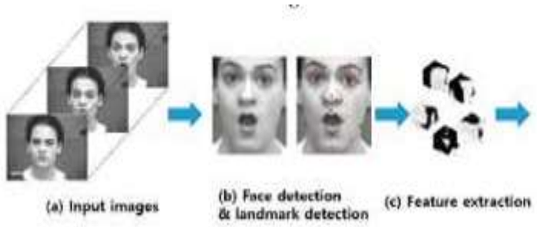

Figure: Feature extraction

Neural networks are often organised using a layered structure. An activation function is stored in each node and the nodes in a given layer are connected to one another via communication. Patterns are taken in by the input layer and sent via weighted connections to the network's hidden layers, where the processing takes place. Face and facial component recognition using the viola-Jones technique is the first step in the facial expression identification system's three-step process: (1) Image Pre Processing; (2) Facial Feature Extraction; and (3) Facial Feature Classification with a Convolutional Neural Network. Kera's is a free and open-source Python neural network toolkit that may be used for reprocessing, modelling, evaluation, and optimization. This is often handled by the backend when working with high-level APIs. The loss and optimizer functions, as well as the fit function, are designed to be employed throughout the model construction and training operations. Tensors and the TensorFlow backend were specifically designed for convolution and other low-level calculations. We use the following Python packages for a variety of tasks, including reprocessing, modelling, optimization, testing, and presenting rated emotional states. The model is built up in layers, beginning with an image reprocessing layer and continuing through a convolution layer, pooling layer, flatten layer, activation layer, and finally a dense layer. The proposed system's initial step entails performing image reprocessing, Face Detection, and FPs identification and extraction. The robust Viola-Jones face identification framework is used, which is capable of doing rapid image analysis in real-time. This technique can accurately identify the face regardless of the input picture's dimensions, background, lighting, or spatial transformations. The identification of facial FP is achieved by chaining several classifiers in a method that increases detection performance while decreasing computational costs. Data is assigned to positive or negative categories according to the weighted error derived by linearly adding all the weak classifiers (weight of each learner is directly proportional to its accuracy). When the face has been identified, cropped, extracted, and scaled down to 64 by 64 pixels, the facial features (the eyes and mouth) are recognised, cropped, and extracted from the normalised face image. While retrieving facial features, IJSER is used to reduce them down to 32x64 pixels. As smaller images demand less storage space, training the network is accomplished more quickly. The inclusion of convolution layers will increase accuracy on large datasets. Facial expressions' emotional content is labelled using data taken from a comma-separated values (CSV) file (in pixel format) and converted into images. The training dataset in this example consists of 34,488 images, whereas the testing dataset has 1,250. Emotions including happiness, sorrow, anger, surprise, apathy, contempt, and fear fall within this category. Emotions may be communicated by a variety of facial expressions, such as a raised eyebrow, an expanded mouth, puffier cheeks, wrinkles on the bridge of the nose, or drooping eyelids. A more accurate object classification was achieved by training on a large dataset. The notion of pooling is connected to convolution in deep learning for visual object recognition. The idea is to use a convolutional filter to transform a region of an image into a feature map (or a local neural network feature detector). A 5x5 pixel array's orientation, for instance, might be interpreted as edge properties. Flattening a Photoshop document occurs when all of the layers are merged into one background layer. Adding additional layers to a file might increase the file size, which in turn would need more computing resources to process. Flattening the image or combining some of the layers might help decrease the size of the file. The thick layer of a neural network is where all the typical connections are found. This lowest layer is also the most often used. The dense layer takes the data and outputs it. Based on the weight of the connections between nodes, the degree of inhibition or excitation, and the transfer functions in play, the activation value of one node is passed on to the next. Using the data given by its transfer function, each node sums up the activation values it has been received and then modifies the sum accordingly. Adding Dropout layers to a Kera's network enables its dropout capabilities. In a Dropout layer, a certain number of units from each batch will be discarded based on a hyperparameter the user sets. Do not forget that Kera's treats the input layer as if it were the first layer, therefore the addition operator can't be used on it. One of the most common nonlinearities in neural networks, REL is employed after the convolutional layer and before the max pooling. Specifically, it does this by replacing all of the feature map's negative pixel values with 0. Applying this after the convolutional layer is common practise.

REL in this context is the maximum function (x, 0) applied to the x matrix of the input (a convolved picture). Then, if the x matrix has any negative numbers, REL will change them to zero while keeping the rest of the numbers the same. Because of the convolution, a nonlinear activation function like a tan or sigmoid is generated when REL is used. As an alternative to the traditional stochastic gradient descent approach, Adam is an optimization technique that may be used to retrain a network's weights in an iterative fashion. There have been many efforts to understand human emotions via the use of various forms of automation. Yet, many of them are useless because they lack a solid framework and specific guidelines for implementation. In particular, machine learning systems for monitoring and recognising emotional patterns may be useful for law enforcement organisations, but only if personnel have a strong understanding of the emotion analysis skills and maintain them periodically.

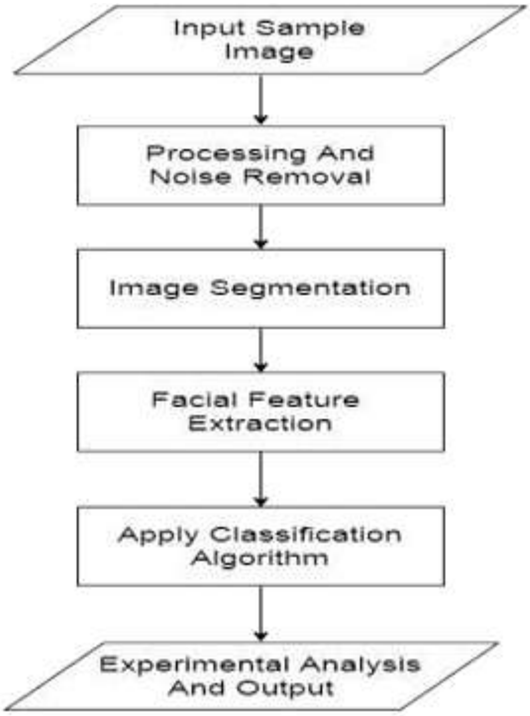

Figure: Emotion Detection Data Flow Diagram

First, get the user's input image, and then filter out any unwanted background noise. Then use the Haar features to recognise only a person's face. When done, the image is compared to the one used during training. Here, you should consult the Python Kera’s library. A convolutional neural network is required for operation (CNN). To function, CNN employs a sequential model. Layers like Conv2D, MaxPooling2D, AveragePooling2D, Dense, Activation, Dropout, and Flatten are also employed. These layers are responsible for making the classification set emotion selection after the approach has been made. What you see before you is the completed product. The feature extraction phase receives the normalised face image after any necessary pre-processing has been completed in order to identify the most important features to use in the subsequent classification stage. In other words, the task of creating a feature vector that adequately characterises the face image falls under the purview of this component. After making these comparisons, the facial image is assigned to one of seven distinct emotions (anger, contempt, disgust, fear, happiness, sadness, surprise).

CONCLUSION & EVALUATION

The lack of sufficient data to develop a comprehensive strategy was the first major obstacle. Which in order to have a framework in nature, needs to be defeated. The most common way to deal with this is through move learning. The starting point for this method was a carefully thought-out strategy, and the model was then fine-tuned using data collected in the real world. Starter studies all corroborated the idea that facial recognition would be more useful than text recognition for highlight extraction. Such systems have proven useful in some contexts. The optimal size of a dataset for machine learning algorithms is a few hundred highlights or segments. The algorithm is able to categorise both the image and its sentiment, and then select the most appropriate emotion to accompany it. The deep learning classifier is preferred because it processes information in stages. And since deep learning algorithms gain access to a vast measure of information to be convincing, they can be useful for less unpredictable issues as well. On average, more than 14 million images are used as a benchmark when developing deep learning models for widespread image recognition. It employed a decision tree for the most effective graphical representation of the underlying pattern analysis used for emotion detection. Each node and layer in the decision tree represents an aspect of the character, while the branch represents the experimental result. The decision tree is beneficial because it facilitates visualisation of the emotion and result interpretation.

A decision tree's logic is simple to comprehend. Ideally, the data would have been sorted into categories representing distinct types of emotion after being analysed for patterns of behaviour and responses. If this could find something that can categorise their use of these methods more simply, it would be organised into trees and sub-trees that reflect the person's emotional state (sad, angry, happy, etc.). Specifically, a retraining technique has been used to ensure that the pattern is well-remembered, and the requirement is met. Any of the following holds true when IJSER 2020 http://www.ijser.org/2020/If you're happy with it, keep going until you reach the last branch. It will stop checking and report that "The emotion cannot be identified" if none of the conditions satisfy the intermediate condition. There is no way to know what this feeling is. Feelings can be hard to put into words. Similar feelings can be communicated in a variety of ways. Various individuals provide diverse sorts of expression for the same kind of feeling. Modern-day machine learning technology can help law-enforcement authority to detect emotion so the machine can understand the emotion of humans and more behave and act like humans. This data for emotion came from different online and offline media. Such as Google, kaggel.com site. Friends and family, random people, etic. This is used Kera's library to initially classify and analyse the emotion and got that data. Then with the help of Haar features and NumPy, it identifies the emotion. And with the help of platform anaconda. It generates the output from the raw data where the result is going to show in real-time. The hierarchical data mining procedure like decision tree helps to generate probability decision by calculating various probability decisions by calculating various characteristic which is initially used to identify the emotion pattern. Along with offline and online data collection, it also conducted an effective field study to gather more people and various kinds of people and various emotional deferent expressions lots of different faces. In online data collection, the data set is taken from kaggel.com. They provide quality data sets. They converted the images into pixel grayscale and use the numerical number of the images. So, it gives the quality data and the batter result.

Both of the experts believed that this analysis of sentiment could help identify emotion more accurately and help to take accurate actions on behalf of errorless computation emotion, data mining can facilitate accurate expression patterns enabling machines to find and act more like humans effectively. To determine the emotion expression patterns this thesis is created or framework with comprehensive research and field works. This followed the framework step by step to get the expected outcome. To follow the framework and to identify the emotion expression patterns more effectively and used deep learning CNN algorithm along with Kera's, TensorFlow, and retraining concepts. With these techniques, it was possible to identify emotions, type of emotion in the real image. To delineate the result and procedures more visually and this has also introduced decision tree techniques which helps to decide which emotions percentage is high and which emotions percentage is low. Now the high percentage of emotions get the most possible accurate emotions. And the low percentage of emotions get the low chance of existence. With this discovery, it is now possible to determine accurate emotions. And machines can identify emotion more accurately and on behalf of that, they can give a proper reaction and also can help to prevent the same unwonted occurrence. This machine can also become the replacement of a human.

CONCLUSION

An experienced human can often identify another human's emotions by analysing and looking at him or her. However, in this modern age machines are becoming more intelligent. For the time been machines are trying to act more like humans. If the machine has been trained on how to react on behalf of the human sentiment at that time. Then the machine can behave and act like a human. On the other hand, if the machine can identify the emotion it can prevent lots of occurrences too. With increased proficiency and errorless computation emotion, data mining can facilitate accurate expression patterns enabling machines to find and act more like humans effectively. To determine the emotion expression patterns this thesis is created or framework with comprehensive research and field works.

This followed the framework step by step to get the expected outcome. To follow the framework and to identify the emotion expression patterns more effectively and used deep learning CNN algorithm along with Kera's, TensorFlow, and retraining concepts. With these techniques, it was possible to identify emotions, type of emotion in the real image. To delineate the result and procedures more visually and this has also introduced decision tree techniques which helps to decide which emotions percentage is high and which emotions percentage is low. Now the high percentage of emotions get the most possible accurate emotions. And the low percentage of emotions get the low chance of existence. With this discovery, it is now possible to determine accurate emotions. And machines can identify emotion more accurately and on behalf of that, they can give a proper reaction and also can help to prevent the same unwonted occurrence. This machine can also become the replacement of a human.

REFERENCES

1. *Wang, Jiawei Zeng, Shi Guang Shan, Chu Xilinx Chen, ‚MULTI-TASK LEARNING OF EMOTION RECOGNITION AND FACIAL ACTION UNIT DETECTION WITH ADAPTIVELY WEIGHTS SHARING NETWORK,' in IEEE, 2019*
2. *Ninad Mehendale, ‚Facial emotion recognition using convolutional neural networks (FERC),' 18 February 2020*
3. *James Pao, ‚Emotion Detection Through Facial Feature Recognition,' in International Journal of Multimedia and Ubiquitous Engineering, November 2017*
4. *Jonathan, Andreas Paestum Lim, Pauline, Gede Putra Kusuma, Amalia Zahra, ‚Facial Emotion Recognition Using Computer Vision,' in Indonesian Association for Pattern Recognition International Conference (INAPR) IEEE, 31 January 2019*
5. *Renuka S. Deshmukh, Vandana Jagtap, Shilpa Pagoda, ‚Facial emotion recognition system through machine learning approach,' in International Conference on Intelligent Computing and Control Systems (ICICCS) IEEE, 11 January 2018*
   6. Hyeon-Jung Lee, Kwang-Seok Hong, ‚A Study on Emotion Recognition Method and Its Application using Face Image,' in International Conference on Information and Communication Technology Convergence (ICTC) IEEE, 14 December 2017
   [13] T. K. Senthilkumar, S. Rajalingam, S. Manimegalai, V. Giridhar Srinivasan ‚Human Facial Emotion Recognition Through Automatic Clustering Based Morphological Segmentation And Shape/Orientation Feature Analysis,' in IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 08 May 2017

   [14]. Tribade, Saeed & Meng, Honeying& Swash, M. & Pleva, Matus &Jahar, Jozef, ‚Facial Expression Emotion Detection for Real-Time Embedded Systems,' January 2018 IJSER Piotrkowska, Magda, Wrobel, Monika, ‚Basic Emotions,' in Springer International Publishing AG, 15 July 2017

   [15]. Ninad Mehendale ‚Facial emotion recognition using convolutional neural networks (FERC),' in Springer Nature Switzerland AG, 18 February 2020

   [16]. Victor M. Alvarez, Ramiro Velázquez, Sebastián Gutierrez, Josué Enriquez-Zarate ‚A Method for Facial Emotion Recognition Based on Interest Points,' in International Conference on Research in Intelligent and Computing in Engineering (RICE), 25 October 2018

   *[17]. Byoung Chul Ko, ‚A Brief Review of Facial Emotion Recognition Based on Visual Information,' 30 January 2018 *18+. Dumas, Melanie, ‚Emotional Expression Recognition using Support Vector Machines,' July 2001*

   [19].Muzammil, Abdulrahman, , Facial expression recognition using Support Vector Machines,' in 23nd Signal Processing and Communications Applications Conference (SIU) IEEE, 22 June 2015