VISVESVARAYA TECHNOLOGICAL UNIVERSITY

Jnana Sangama, Belagavi – 590 018.

PROJECT PHASE – I REPORT

on

"EMOJIFIER"

Submitted in partial fulfillment of the requirement for the curriculum of the 7th Semester

Bachelor of Engineering

in

Computer Science and Engineering

by

SYED MOHAMMAD IMAD	**:**	**1VI19CS113**
RANJINTH SINGH S	**:**	**1VI19CS081**
SANTHOSH S	**:**	**1VI19CS092**
ROHAN TELKAR	**:**	**1VI19CS086**

Under the supervision of

Mrs. RACHITHA M V

Assistant professor

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

VEMANA INSTITUTE OF TECHNOLOGY

BENGALURU – 560 034

2022 - 2023

Karnataka ReddyJana Sangha®

VEMANA INSTITUTE OF TECHNOLOGY

Koramangala, Bengaluru-34.

(Affiliated to Visvesvaraya Technological University, Belagavi)

Department of Computer Science and Engineering

Certificate

This is to certify that the project (phase-I) entitled "EMOJIFIER" **is** a bonafide work carried out jointly by **SYED MOHAMMAD IMAD (1VI19CS113), RANJITH SINGH S (1VI19CS081), SANTHOSH S (1VI19CS092)** and **ROHAN TELKAR (1VI19CS086),** during the academic year 2022-23 in partial fulfillment of the requirement for the 7th Semester course work for theof **Bachelor of Engineering** in **Computer Science and Engineering** of the **Visvesvaraya Technological University**, **Belagavi.** It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report. The project phase - I report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the said degree.

Guide	**HOD**	**Principal**
Mrs. Rachitha MV	Dr. M. Ramakrishna	Dr. Vijayasimha Reddy. B. G

ACKNOWLEDGEMENT

We sincerely thank **Visvesvaraya Technological University** for providing a platform to dothe project phase - I.

Firstly, we would like to express our deep sense of gratitude to our institute "**Vemana Institute of Technology**" that provided us an opportunity to do a project phase - I entitled "**EMOJIFIER**".

We thank **Dr. Vijayasimha Reddy B G,** Principal, Vemana Institute of Technology, Bengaluru for providing the necessary support.

We would like to place on record our regards to **Dr. M. Ramakrishna,** Professor and Head,Department of Computer Science and Engineering for his continued support.

We would like to thank our project coordinators **Mrs. Mary Vidya John,** Assistant Professor and **Mrs. Brundha Elci J.,** Assistant Professor, Dept. of CSE for their support and coordination.

We would like to thank our project guide **Mrs. RACHITHA M V,** Assistant Professor, Dept. of CSE for her continuous support and valuable guidance towards successful completion of the project phase – I.

We would be failing in our duty if we do not thank the faculty members, batch mates, lab staffs, technicians and family members for their constant support and guidance.

Date:

Place: Bengaluru

SYED MOHAMMAD IMAD	**1VI19CS113**
RANJITH SINGH S	**1VI19CS081**
SANTHOSH S	**1VI19CS092**
ROHAN TELKAR	**1VI19CS086**

ABSTRACT

Emojis are small images that are commonly included in social media text messages. The combination of visual and textual content in the same message builds up a modern way of communication. Emojis or avatars are ways to indicate nonverbal cues. These cues have become an essential part of online chatting, product review, brand emotion, and many more. It also led to increasing data science research dedicated to emoji-driven storytelling. With advancements in computer vision and deep learning, it is now possible to detect human emotions from images. In this project, we will classify human facial expressions to filter and map corresponding emojis or avatars. Emojifier is a software which deals with the classification of facial expressions, text and speech into Emojis or Avatars.

TABLE OF CONTENTS

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

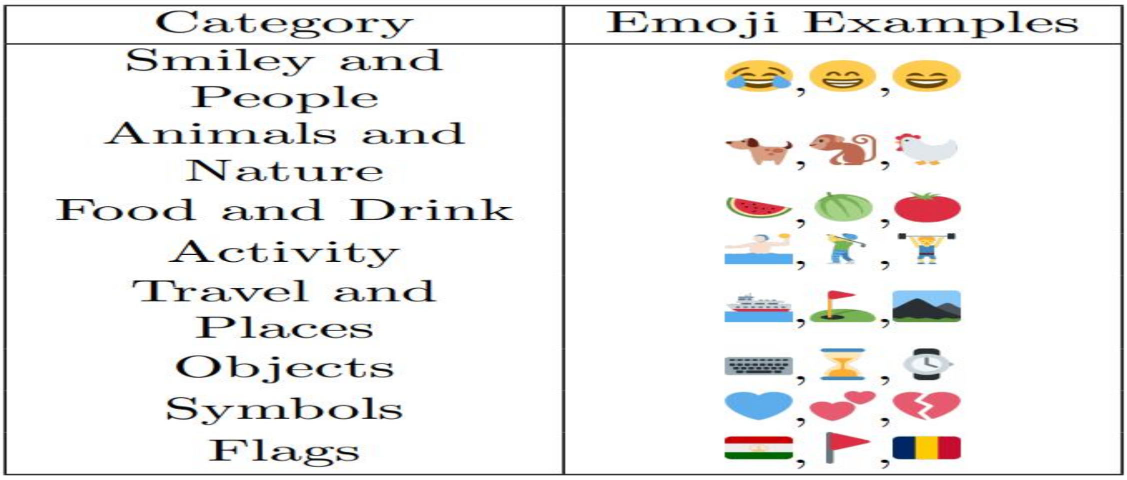
LIST OF ABBREVIATIONS

Acronyms	Abbreviations
Bi-LSTM	Bi-directional long term short memory
CNN	Convolutional Neural Network
ML	Machine learning
NLP	Natural Language Processing
Open CV	Open source computer vision
RNN	Recurrent neural network
SVM	Support Vector Machine
VS code	Visual studio code
GPU	Graphic processing unit
TPU	Tensor processing unit
OST	Object storage target
AR	Augmented reality
API	Application program interface
ICML	International Conference on Machine Learning

CHAPTER 1

INTRODUCTION

Emojis are the modern-day equivalent of emoticons. The necessity for them developed from the difficulty of conveying emotions and expressions in written form. The Unicode Consortium standardized these two-dimensional visual representations of commonplace things as part of Unicode 6.0 in 2010. Emoji spread rapidly over the world, becoming an integral component of Western popular culture in particular. Practically every network and messaging app now uses it. One of the most important functions of emojis in internet communication is the expression of emotion. The number of emojis has grown to 2,666 as of June 2017, the latest data available on Emojipedia. This presents difficulties for programs that list them on portable devices with limited screen real estate, such as mobile phones. To get around this problem, most devices' emoji keyboards have the classifications shown in Figure 1.1.



Category	Emoji Examples
Smiley and People	😂, 😁, 😄
Animals and Nature	🐕, 🐒, 🐓
Food and Drink	🍉, 🍈, 🍅
Activity	🏊, 🏌, 🏋
Travel and Places	🚢, ⛳, 🏞
Objects	⌨, ⌛, ⌚
Symbols	💙, 💕, 💔
Flags	🇹🇯, 🚩, 🇷🇴

Fig. 1.1: Emoji Categories

The use of emojis, which are standardized sets of small graphical glyphs showing anything from smiling faces to foreign flags and were first presented in 1997, has witnessed a significant surge in usage in social media over the past decade. Emojis were first introduced in 1997. The 'Face with Tears of Joy' emoji was selected as the Oxford Dictionary's Word of the Year for 2015. This was due to the fact that the use of emojis increased by more than 800% during the course of the year. The Oxford Dictionary declared 2015 the year of the emoji. Over ten percent of the postings on Twitter and more than half of the content on Instagram contain at least one emoji. Because of their widespread adoption and popularity, they have been the focus of a significant amount of scholarly and non-scholarly investigation in the fields of language and social communication, as well as natural language processing (NLP).

The lack of manually annotated data hinders the progress of many natural language processing jobs. As a result, models have been using co-occurring emotional expressions for distant supervision in social media sentiment analysis and related tasks in order to acquire helpful text representations before modelling these tasks directly. For instance, cutting-edge techniques for analyzing social media data rely on a library of positive and negative emoticons to teach their algorithms how to interpret user feedback. Similarly, prior studies have mapped hashtags like #angry, #joy, #happytweet, #ugh, #yuck, and #fml into emotional categories for study.

In the field of social sciences, a significant amount of attention has been paid to the practice of employing emojis on mobile platforms as a means of conveying one's emotional state. Emojis are commonly regarded as a means of conveying emotions; however, recent research has shown that they are also being used as tools to express relationally helpful roles in discussion. This finding is rather intriguing. Emojis have been shown to be culturally and contextually bound, and it has been demonstrated that this leaves them subject to reinterpretation as well as misinterpretation. These discoveries have led the way for several formal examinations of the semantic features of emojis.

In many cases, a model can achieve higher performance on the goal task with distant supervision. In this research, we demonstrate that improving the models' performance on benchmarks for identifying sentiment, emotions, and sarcasm may be achieved by expanding the distant supervision to a more diverse set of noisy labels.

Concurrently, we have seen a rise in interest in the application of natural language processing to data derived from social media. Many of the contemporary NLP systems that are applied to social media rely on representation learning and word embeddings. Such systems frequently rely on pre-trained word embeddings, which can, for example, be obtained via word2vec or GloVe. These two resources are both available online. However, neither resource has the full set of Unicode emoji representations, which leads one to believe that a great number of social NLP applications could be enhanced by the incorporation of more robust emoji representations. In this work, we announce the availability of emoji2vec, which is an embedding for emoji Unicode symbols that was learned from the description of those symbols in the Unicode emoji standard. In addition, we offer a qualitative study by researching some examples of emoji analogies and visually representing the area in which emojis can be embedded.

The use of emojis is one approach to convey nonverbal messages. These indicators have rapidly become an indispensable component of a wide variety of activities, including online talking, product reviews, brand emotions, and many others. Additionally, it resulted in an increase in the amount of data science research that was devoted to emoji-driven storytelling. This technology allows us to grasp the emotions and sentiments of a person without having to focus on their face and can also be used to generate image filters. It does both of these things by utilizing a neural network. The CNN recognition technique was utilized in the training process for the Machine Learning model.

1.1 SCOPE

Emotional and semantic emoji evolved from emoticons. Individual conditions, culture, and platforms affect emoji use. Ambiguity and misunderstanding can emerge in different cultural contexts. From the perspectives of many fields (communication, computing, behavioral science, marketing, and education), this Project comprehensively combs the research topics, methods, and tools used in emoji studies, systematically summarizes the research status of emoji in various fields, and proposes new perspectives for future emoji research, such as emotional association, use preference, new modalities, and social impacts. and sentiments of a person without having to focus on their face and can also be used to generate image filters. It does both of these things by utilizing a neural network.

Fig. 1.2 : Emoji face stimuli

1.2 OBJECTIVES

- To open up conversations about emotion recognition systems: from the science behind the technology to their social impacts.
- To develop a model using filtered data gives better predictions.
- To promote public understanding of these technologies and citizen involvement in their development and use.
- To bring public understanding and awareness in the development of the emotion recognition systems and their social impact.
- To identify the intensity of pain of a deaf patient. For example: It can be used by Video conferencing doctors.

1.2.1 Plan of action for the project

Table 1.1 : Timeline Chart

Task	October	November	December	January	February	March	April	May
Problem Formulation								
Synopsis Submission								
Research and Tools procurement								
Building Prototype								
Testing the prototype								
Customizing the prototype								
Final Testing of prototype								
Report Submission								

Stage 1 – In this stage, we done planning of doing conversion of Facial Expression To Emoji, Speech To Emoji, Text To Emoji ML project.

Stage 2 – In this stage, the team identified the software requirements for the project, drafted a plan and collected 4 reference papers to gain information that is required to start the project.

Stage 3- In this stage, the team gained knowledge on neural networks and how to use them. Artificial Neural networks for raw data and Convolutional Networks.

Stage 4 - The project was proposed to the college and reviewed by the panelists.

Stage 5 – In this stage, we started with the documentation work and drafted the report for project phase-1.

Stage 6- Developing a working prototype and check the initial accuracy.

Stage 7- Customizing the prototype based on the results we get during the initial test.

Stage 8- Final testing is done after implementing all the changes

Stage 9- Submitting the final report of the project.

1.2.2 Current status of project

The deadlines set to complete the project phase-1 is end of December. As mentioned earlier, the project phase-1 consists of devising a problem statement, analyzing the requirements, and drafting the report, this is to be successfully completed by December. The initial framework is to be completed by the end of December. This gives us more time to focus on the implementation of the main project so that we can get better and accurate results as we planned to spend four months to build the project.

1.2.3 Proposed plan for completion

- **Data collection**: Storing the facial expressions from premade datasets like FER-2013 and also by adding our own facial expressions, using it as a training set to predict Emojis.
- **Data Pre-processing**: This was converted into a dictionary format where the dictionary key is the year and, the data in step 1 was combined with data of this

  Data Cleaning: The CSV file created in step 2 was cleaned to remove null values and improper data. A new resultant CSV file was created.
- **Feature Engineering and Model Creation**: Tried various algorithms, like Convolutional Neural Network, Bi-directional Long short term memory, HAAR cascade classifier gave best performance.

1.2.4 Outline of the chapters

- **Chapter 1**: Introduction - In this chapter we have a brief introduction to the project. It includes scope of the problem statement and the objectives of the project like plan of action, current status of project and proposed plan for completion of project.
- **Chapter 2**: Literature Survey - In this chapter we look at different survey/reference papers that we have considered that has helped for completion of our project. We have identified the advantages and limitations of each survey paper. This includes a comparative analysis of the papers to understand the how each proposal is different from the other.
- **Chapter 3:** System Requirements - In this chapter we have determined all the requirements of the project that include, functional, non-functional, hardware and software requirements.

- **Chapter 4**: Design methodology - In this chapter we understand the system architecture and the dataflow diagrams to visualize the workflow.
- **Chapter 5**: Module Description - In this chapter we elucidate the working of eachmodule that is built to develop the system.
- **Chapter 6**: Summary- In this chapter we have summarized all the work that we have done in the first phase of the project.

CHAPTER 2

LITRERATURE SURVEY

[1] Emotion Recognition Based Emoji Retrieval Using Deep Learning by Swati Srivastava , Prateek Gupta and Pravendra Kumar Department of Computer Engineering & Application GLA University Mathura, India.

In this paper, they proposed a deep learning model to classify facial expressions from the images. Then they mapped the classified emotion to a corresponding emoji or an avatar. They built a convolution neural network to acknowledge facial emotions. They trained their model on the FER2013 dataset. Then mapping of those emotions with the corresponding emojis or avatars have been performed. Using OpenCV's HAAR cascade xml, they obtained the bounding box of the faces within the webcam. Then they feed these boxes to the trained model for classification. In this will build a convolution neural network structure and train the model on FER2013 dataset for Emotion recognition from images. The FER2013 dataset (facial expression recognition) consists of 48*48 pixel grayscale face images. The images are centered and filled with an equal amount of space. This dataset consists of facial emotions of following descriptions; angry, disgust, fear, happy, sad, surprise, natural. The training set consists of 25000+ images and the public test set consists of 3500 images.

They used image processing techniques such as reshape, resizing, converting to greyscale, and standardization. NumPy and pandas library are used for implementation. With the help of power vectorization array and pandas data frames, images have been processed whenever required the images with the help of NumPy arrays and generate the output by pandas. Preprocessing results in an improved image that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. First they have reduced the noise of images with the help of auto-encoding algorithm which help in reduction of unwanted data. It also helps to reduce dimensionality of data. Then they have converted the images into grayscale. They have used image segmentation through non-contextual thresholding and contextual segmentation so that it can convert part of an image into multiple parts and separating foreground from background so that emotion on the face in an image can be easily detected. With geometric transformation, positions of pixels in an image are modified.

- **Methodology :** They developed an improved emotion recognition model for facial expression images. They have proposed a convolutional neural network based deep learning model which is tested on FER2013 dataset.

- **Advantages:** The proposed model has a accuracy of 87%. The image detection is really fast with a very high success rate. This proposed model which will detect the facial expressions and map those emotions on the faces with the corresponding emojis or avatars.
- **Disadvantages:** It only works For Still images and does not give accurate results for motion pictures/videos. The efficiency involved in the preprocessing steps is not up to the mark.

[2] Emojify –Create your own emoji with Deep Learning by Payas Doshi, Priyanshi Sethi, Pulkit Sharma, Mahaveer Jain International Research Journal of Engineering and Technology.

They had builded a convolution neural network to recognize facial emotions. They had trained their model on the FER2013 dataset. Then we'll map those emotions with the corresponding emojis or avatars. Fer2013 contains approximately 30,000 facial RGB images of different expressions with size restricted to 48×48, and the main labels of it can be divided into 7 types: 0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral. The Disgust expression has the minimal number of images – 600, while other labels have nearly 5,000 samples each.In this deep learning project, they had classified human facial expressions to filter and map corresponding emojis or avatars. Created a folder named emojis and saved the emojis corresponding to each of the seven emotions in the dataset. The trained model is tested on a set of images. Random images are introduced to the network and the output label is compared to the original known label of the image. Parameters used for evaluation are F1 score, precision and recall. Precision is the proportion of predicted positives that are truly positives.

Methodology:

1. Build a CNN architecture. Here they are importing all the required libraries needed for their model and then they are initialising the training and validation generators i.e., they are first rescaling all their images needed to train their model and then converting them to grayscale images.

2. Train the model on Fer2013 dataset. Here they are training their network on all the images they have i.e., FER2013 dataset and then saving the weights in model for the future predictions. Then using OpenCV harassed xml to detect the bounding boxes of face in

3. webcam and predict the emotions.

Advantages: It is designed to receive voice commands, reduce typing difficultly, and provide output in both text and voice formats. The predicting the emojy based on the emotion at an accuracy of 90%. use of emojify in chatting world. people can communicate with their own customisable emoticon. This project will recognize one’s current emotion and convert that emotion's emoji so that the customer gets emoji of their face and use it in chatting.

Disadvantages: The Graphical user interface is not user friendly and the accuracy attained is not very high. It can only be used with images.

Tools Used:

Google Collab supports both GPU and TPU instances, which makes it a perfect tool to train the model on large datasets. They have also used various data science related libraries like koras, TensorFlow, OpenCV, matplotlib, NumPy etc. For the purpose of building the keras model they have used sequential modelling technique. VS Code is used for overall development as a standard platform.

[3] Anon-Emoji: An Optical See-Through Augmented Reality System for Children with Autism Spectrum Disorders to promote Understanding of Facial Expressions and Emotions by Ran Sun Harald Haraldsson1 from Cornell Tech Yuhang Zhao Serge Belongie from Cornell University.

Based on their observations, they designed the system of A non Emoji. Their system consists of a head tracker that the subject wears on the head and a system running on the Magic Leap One headset. When the headset picks up the head tracker either through image tracking or electromagnetic tracking, Their system tracks the position and orientation of the person's head and renders an emotion presenting 3D emoji around it so as to occlude his/her face. They chose emojis for two main reasons: its nature in expressing non-verbal information; its strength in concealing effects under OST AR settings. The emotional information they bear is widely recognized and easy to comprehend. As they are in the rough shape of a head, they make sense to the viewers when overlayed on the head of a subject. Finally, emojis are generally bright yellow in color, which their experience tells us is ideal for occluding objects in OST AR displays. In the future, they will implement a separate process runs in the background on the device which aims to perform facial landmark detection and sentimental analysis to extract the facial expression of the subject, map it to a certain emoji, and change the renderings.

Methodology: Their system consists of an AR headset and a head tracker. Viewers are required to wear the AR headsets, while subjects only wear head tracker around their heads. The head tracker helps identify the position and rotation of the subject's head. Once the tracker is picked up by the system, a virtual rendering of 3D emoji model will be rendered around the subject's head. The emoji model will obscure most visual information of the subject's face from all directions.

Advantages: It can be used for kids with Autism disorder and help them learn better through use of emojis. The system tracks the position and orientation of the person's head and renders an emotion presenting 3D emoji around it so as to occlude(close up) his/her face.

Disadvantages: OST headsets are designed for indoor purposes. The design would work well only in indoor settings without strong light coming through the headset. Although the general intention of AR(Augmented reality) is to add objects to a real environment, it can also remove objects. However, including real world objects is not one of the strengths of OST AR displays.

Tools used: Magic Leap One Headset, OS version 0.95.2, MLSDK 0.20.0, Unity, OpenCV for Unity.

[4] Facial Emoji Recognition by N. Swapna Goud(Assistant Professor), K. Revanth Reddy, G. Alekhya, G. S. Sucheta CSE Department, Anurag Group of Institutions, Telangana, India.

They following steps are:

1. Decomposing an image.

Images are composed of pixels and these pixels are nothing more than numbers. Often it is considered that the Coloured images can be divided into three colour channels, which are :red, green, and blue and each channel is represented by a grid (2-dimensional array). Each cell in the grid stores a number between 0 and 255 which denotes the intensity of that cell.

2. Importing Necessary Libraries

The libraries like Numpy, Pandas, Matplotlib and SKlearn are imported in this project.

3. Define Data Loading Mechanism

They had defined the load_data() function which will efficiently parse the data file and extract necessary data and then convert it into a usable image format. All the images in their dataset are 48x48 in dimensions. Since these images are gray-scale, there is only one channel. They will extract the image data and rearrange it into a 48x48 array. Then convert it into unsigned integers and divide it by 255 to normalize the data. 255 is the maximum possible value of a single cell and by dividing every element by 255, they have ensured that all values range between 0 and 1. They have checked the Usage column and store the data in separate lists, one for training the network and the other for testing it.

4. Defining the model.

They have used Keras to create a Sequential Convolutional Network. Which means that neural network will be a linear stack of layers.

5. Callback functions

Callback functions are those functions which are called after every epoch during the training process.

6. Training the model

The Model has been trained based on the Datasets provided.

7. Test the model

The project is started off by defining a loading mechanism and loading the images. Then a training set and a testing set are created. After this a fine model and a few callback functions are defined. The basic components of a convolutional neural network are considered and then they training is done to the network.

Methodology: Facial expressions can be described as the arrangement of facial muscles to convey a certain emotional state to the observer in simple words. Emotions can be divided into six broad categories—Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral. Train a model to differentiate between these, train a convolutional neural network using the FER2013 dataset and will use various hyper-parameters to fine-tune the model.

Advantages: It can be used to denote a person’s stress level in a hassle free way.Robust spontaneous expression recognizers in the model can be developed and deployed in real-time systems.

Disadvantages: This works only for images and can not classify text or speech like their project.

[5] Real-Time Facial Expression Recognition Based on CNN by Keng-Cheng Liu, Chen-Chien Hsu, Wei-Yen Wang, Hsin-Han Chiang Department of Electrical Engineering National Taiwan Normal University Taipei, Taiwan.

In this paper, the proposed method aims to improve the accuracy of real-time facial expression recognition. The method is divided into three steps:

1) obtain and input the images to the CNN architecture for recognition;

2) obtain the results of facial expression recognition;

3) average the recognition result with the previous output and re-output.

In this way, real-time recognition can be achieved through integrating the CNN architecture and the webcam. Moreover, overall robustness and accuracy of facial expression recognition are greatly improved by using the proposed method compared to those obtained by only the convolution neural network (CNN).

For face detection, they used a Logitech C920 webcam with the Open CV face capture program and the parameters from the face training set haarcascade_frontalface_alt.xml. The detection was programed in Python on the Anaconda platform to achieve a detection rate of about 10 images per second. This step was followed by grayscale conversion and resizing for each image to immediately and quickly input the captured images into the trained framework.

Methodology: They derived from the average of the current recognition result and the previous recognition result because the system considers both the CNN architecture and the influence of the environment of the captured image. Each image has 7 weights indicating different expressions, which are recorded and averaged with the weights of the previous image. Subsequently, the largest output is therefore regarded as the prediction result. It is worth noting that the proposed average weighting method is used when the weights are produced from the second identification. Because the weights are averaged between the current and the prior recognition, the error is accordingly reduced. The accuracy of the original CNN architecture complements each other to enhance the overall performance. Furthermore, if a webcam is employed, an effective real-time facial expression recognition system can therefore be achieved.

Advantages: Because of the average weighting method, facial expression recognition results become more robust from frame to frame. As a result, the accuracy of facial expression recognition is improved. Experimental results have shown that the proposed facial expression recognition system is more reliable than the traditional CNN approach. Max pooling is employed for the pooling of each layer.

Disadvantages: This model has less accuracy and low quality image recognition.

[6] Exploiting Deep Neural Networks for Tweet-based Emoji Prediction by Andrei Catalin Coman, Giacomo Zara1, Alessandro Moschitti University of Trento, Trento, Italy and Yaroslav Nechaev , Gianni Barlacchi Fondazione Bruno Kessler, Trento, Italy.

Their model CNN has been used to solve various types of problems. One of the first applications of this neural-architecture was in the visual domain, where they were employed for image and video recognition. However, their versatility has led them to be used in Recommendation Systems and even in Natural Language Processing tasks. In contrast to classic Multilayer Perceptron Neural Networks, CNNs have distinguished themselves through three essential characteristics, namely:

number of parameters to train: in classic neural network architectures, i.e. those with a lot of dense hidden layers and units, the number of parameters to be trained grows really fast. With CNNs instead, the amount of train parameters is given by the size and quantity of convolution filters, which in some cases are drastically less.

parameters sharing: a feature detector that’s useful in one part of the sentence is probably useful in another part of the sentence.

sparsity of connections: in each convolution layer, each output value is depends only on a small number of inputs.

Methodology: They present the Neural Network models they used to perform their emoji predictions. The first model is an architecture based on RNNs, where the recurrent cell consists of a Bi-LSTM.As second model they decided to implement a CNN, since over the years it has proved to be effective in the Natural Language Processing area. Some other concepts are also exposed including the last layer used for predictions, the loss function applied for the train, the regularization techniques employed to contain overfitting and finally the strategy adopted to stop the train.

Advantages: The main advantage is it uses FastText embeddings over Word2Vec is to take into account the internal structure of words while learning word representations, which could be very useful for morphologically rich languages, and also for words that occur rarely. The Deep learning model can tackle problems that traditional machine learning models cannot.

Disadvantages: Not much flexibility. No option to speed up using GPU. Can be used only for text classification and word embeddings. The Deep learning works only with large amounts of data.

[7] Transformation of Facial Expression into corresponding Emoticons by Ankur Ankit, Dhananjay Narayan, Alok Kumar International Journal of Engineering and Advanced Technology (IJEAT)

Their proposed model will detect a face using API and feature extraction is done through HAAR Cascade. Emotions are classified from the extractions through SVM. The Emojis are later superimposed over the faces according to the matching emotion exhibited by the subject.

API implementation: An API acts as an interface between an operating system, application and the user. The API design plays a significant role on its usage . An API is designed in such a way that it hides the background details of modules from the users who do not have the knowledge of complexity of the modules. Thus, API facilitates the user-friendly interface. A camera-based API can be used which automatically detects the face of the subject(s) regardless of the background and send this image to the model for processing after which the emoji will be superimposed over the face.

The image that is supplied by the API is then provided to the HAAR cascade in which some dataset has been given for training the data. For the development of a working model, they will use two datasets: Cohn-Kanade (CK+) and Japanese Female Facial Expression (JAFFE) . HAAR-Like features have high accuracy to detect faces from different angles.

Support vector machine: Support Vector Machine is a supervised machine learning algorithm that is used for classification as well as regression problems. The SVM is used in many pattern analysis tasks with support of binary classifier that differentiates between the classifications of the expressions. It works by classifying data through the use of assessment of an optimal hyper plane which separates one class's data points from the other.

Methodology: The idea of the proposed system is to employ an API that will detect the face after which the image can be processed using HAAR cascade for facial feature extraction. SVM Classifier is then used to categorize the emotions into its seven distinct types. Using HAAR of OpenCV package, the corresponding emojis of the emotions can get superimposed over the subjects' faces. In any camera module of any leading social networking apps, the use of APIs can reduce the processing time for face detection for which they have their in-built face detection algorithm which can detect the face smoothly and followed by which the emoticons can be implemented over the faces as filters.

Advantages: very fast at computing features due to the use of integral images. They are also very efficient for feature selection through the use of the AdaBoost algorithm. It works really well with a clear margin of separation. It is effective in high dimensional spaces.

Disadvantages: The downside is that it tend to be prone to false-positive detections. It doesn't perform well when they have large data set because the required training time is higher.

[8] Mapping of human facial expressions to emojis using Deep learning by Parth Vishe, Student, Dept. of Electronics and Telecommunication. Engg, Pune Institute of Computer Technology, Pune, Maharashtra, India.

- **Input the dataset:** The sample images from the FER 2013 dataset that are used to classify emotions. These Images are categorized based on the emotion shown in the facial expressions such as happiness, neutral, sadness, anger, surprise, disgust, fear.
- **Data pre-processing and applying augmentation Strategies:** Image data augmentation is used to expand the training dataset in order to improve the performance and ability of the model to generalize. Images are rescaled from [0,255] to [0,1] using the ImageDataGenerator python module. Benefits of this are It treats all images in the same manner and some images are high pixel range while some are low pixel range. The images are all sharing the same model, weights and learning rate. The high range image tends to create stronger loss while low range creates weak loss and the sum of them will all contribute to the back propagation update. Using typical learning rate: When they reference the learning rate from other's work, they can reference their learning rate directly if both works do the scaling preprocessing over images data set. Otherwise, higher pixel range image results in higher loss and should use a smaller learning rate, lower pixel range image will need a larger learning rate.
- **Neural Network architecture:** After pre-processing the database, the next step is to build a convolutional neural network. The convolution layer consists of input layers, hidden layers, and output layers. Depending on the structure of the neural network add convolutional layers with filters.
- **Methodology:** Their system treats all images in the same manner: some images are high pixel range while some are low pixel range. The images are all sharing the same model, weights and learning rate. The high range image tends to create stronger loss while low range creates weak loss and the sum of them will all contribute to the back propagation update .Using typical learning rate: When they reference the learning

rate from other's work, they can reference their learning rate directly ifboth works do the scaling preprocessing over images data set.

- **Advantages:** it possible to use the software on multiple GPUs or CPUs. The google colab used allows anybody to modify the code according to their will.
- **Disadvantages:** No windows support. It has a very limited set of features for Windows users. The tensorflow used is comparatively slower and less usable compared to its competing frameworks. Google colab has a limited space and time.

[9] Emojify: Emoji Prediction from Sentence by Chen Huang, Xueying (Shirley) Xie, Boyu (Bill) Zhang Stanford University.

Their model extracts 167,685 sentence - emoji pairs for training. However, the dataset is heavily unevenly distributed, where emoji has over 50% representation power of the whole dataset. So they have done several data preprocessing steps before training. Noise removal, filter out emojis which has less than 10000 correspondence sentence. Stop emojis, like the stop words technique in NLP, remove high frequent emojis which are everywhere and do not have specific semantic meaning. Data un-bias, equalize the number of sentences for each emoji. After the data pre-processing, the dataset is reduced to 13251 valid examples which belongs to 13 emoji categories.

Word Embedding: BoW-TFIDF Instead of representing the sentences with matrix of corpus and counts like we've seen in class, they can employ Bag of Words representation with TD-IDF trying to capture more indicative keywords in a sentence. The dictionary size is 1834 after stop words and stemming. They can feed this into Their traditional methods for Naive Bayes and SVM.

Multinomial Naive Bayes Classifier: Then by using a word dictionary they transform texts into word vector via bag of words with TD-IDF as described above. Finally here they apply a Multinomial Naive Bayes Classifier to train the model for text classification. Since Naive Bayes is a simple classifier to use, it acts as a good baseline and starting point to tackle this problem.

Bi-LSTM Classifier: For the RNN model, the first layer is embedding layer, embedding layer will represent each word as a matrix. The embedding layer is loaded from a Pre-trained GLoVe model and the weight is fixed during training.

Methodology: Predicting emojis is more like a sentence classification problem. They first investigate the word embedding techniques to use, then try machine learning algorithms they learned in the class, such as Multinomial Naive Bayes, SVM and Bi-LSTM to do the emoji prediction.

Advantages: It is suitable for solving multi-class prediction problems. If its assumption of the independence of features holds true, the naive bayes can perform better than other models and requires much less training data. Naive Bayes is better suited for categorical input variables than numerical variables. It is easy to implement as they only have to calculate probability.

Disadvantages: The naive Bayes classifier used relies on an often-faulty assumption of equally important and independent features which results in biased posterior probabilities.

[10] EMOJIFY-CREATE YOUR OWN EMOJIS WITH DEEP LEARNING by Sagar Chilivery, Sandeep Pukale, Yashraj Sonawane Vasantdada Patil Pratishthan's College Of Engineering And Visual Arts, India.

Their notion of creating their personal custom designed emojis. Emojify is a software program which offers with the advent of Emoji's or Avatars. The neural community has been an rising software in numerous regions as instance of cease to cease studying this paper primarily based totally on a gadget which implements Convolutional Neural Network and Fer2013 Dataset to hit upon feelings from facial expressions and changing them to personalized emojis. They are constructing a convolution neural community to apprehend facial feelings. They might be education version at FER2013 dataset. Then we'll map the ones feelings with the corresponding emojis or avatars. Fer2013 carries about 30,000 facial RGB pics of various expressions with length limited to 48×48, and the principle labels of it is labelled to be divided into five types: 0=Sad, 1=Surprise, 2=Fear, 3=Happy, 4=Neutral.

Methodology:

1. Build a CNN Architecture. Here they are uploading all of the required libraries wished for their version after which we're initializing the education and validation mills i.e., we're first rescaling all their pics had to teach their version after which changing them to grayscale pics.

2. Train the version on Fer2013 dataset. Here we're education Their community on all the pics they have got i.e.Fer2013 dataset after which saving weights in version for the destiny predictions. Then the use of OpenCV hit upon bounding containers of face in webcam and are expecting emotion.

Advantages: It's ability to execute feature engineering by itself. The predicting the emoji based on the emotion at an accuracy of 90%.

Disadvantages: A lot of training data is needed for it to be effective and they fail to encode the position and orientation of objects.

Tools used

They have used diverse records technology associated libraries like keras, TensorFlow, OpenCV, NumPy etc. For the motive of constructing the keras version they’ve got used sequential modelling technique. VS Code and Anaconda Prompt is used for usual improvement as a common platform.

2.6 COMPARATIVE ANALYSIS

Comparative analysis is the process of comparing items to one another and distinguishing theirsimilarities and differences**.** When a business wants to analyze an idea, problem, theory or question, conducting a comparative analysis allows it to better understand the issue and form strategies in response.

Reference	**Algorithm/ Technique**	**Platform used**	**Performance Metrics**	**Advantage**	**Drawback**
[1]	CNN Algorithm with Deep learning	Jupyter Notebook	Throughput	The image detection is really fast with a very high success rate.	It only works for Still images and does not give accurate results for Motion pictures/videos.
[2]	CNN Algorithm.	Google Collab, VS Code	Accuracy	It is designed to receive voice commands, reduce typing difficulty, and provide output in both text and voice formats.	The Graphical User Interface is not user friendly and the accuracy attained is not very high .It can only be used with images.
[3]	OST AR	OpenCV for	Accuracy	It can be used	The design

	displays	Unity 2.3.4		for kids with Autism disorder and help them learn better through the use of emojis.	would work well only in settings without strong light coming through the headset.
[4]	CNN Algorithm.	Anaconda Platform	Robustness	It can be used to denote a person’s stress level in a hassle free way.	This works only for images and can not classify text or speech like their project.
[5]	CNN Algorithm.	Anaconda Platform with OpenCV.	Accuracy	It denotes the robustness of facial emoji recognition.	This paper does not have a high accuracy
[6]	Bi-LSTM, CNN Algorithm , fastText.	Jupyter Notebook	Functionality	Simple deep neural networks can also reach quite good results by improving them through fine-tuning of hyper-	The Deep Learning approach has generally outperform ed both the baselines.

				parameters, regularization, and optimization of the models themselves.	
[7]	SVM, HAAR	Google Collab, VS Code	Accuracy	Their approach of using APIs instead of neural networks, makes the implementation convenient.	The Accuracy is less compared to the existing deep learning models.
[8]	CNN Architecture	TensorFlow, Keras , OpenCV, Google Collab,	Accuracy	It treats all images in the same manner some images are high pixel range while some are low pixel range. The images are all sharing the same model, weights and learning rate.	Achieves an accuracy of only about 60-65%. Does not work well on people with a beard.
[9]	Multinomial Naive Bayes, LSTM	Anaconda Platform	Accuracy	Naïve Bayes performed very well with a high accuracy	This works only for text classificatio

				of 95% for text classification.	n and not for image or speech classificatio n.
[10]	CNN Algorithm.	Anaconda prompt, VScode	Accuracy	It denotes the robustness of facial emoji recognition.	This paper has less accuracy.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 Functional Requirements

A Functional Requirement is a description of the service that the software must offer. It describes a software system or its component. Requirements are that specifies a function that asystem or system component must be able to perform. The functional requirement describes afunctionality to be made available to the users of the system, characterizing partially its behavior as an answer to the stimulus that it is subjected to. This type of requirement should not mention any technological issue, that is, ideally functional requirements must be independent of design and implementation aspects.

3.2 Non-Functional Requirements

- Reliability: Providing a reliable service for prediction of emojis.
- Security: The data will not be compromised as it will be stored on a securecloud service.
- Performance: Aiming to provide a model which is highly accurate.

3.3 Hardware Requirements

Processor :	INTEL CORE I5
Ram :	8 GB
Processor Speed :	2.4 GHz
System Type :	64-bit/32-bit Operating System
Display :	1920*1080

3.4 Software Requirements

Programming Language :	PYTHON
Operating System :	WINDOWS 10
Software :	JUPYTER NOTEBOOK USING PYTHON 3.7

CHAPTER 4

DESIGN METHODOLOGY

4.1 System Architecture

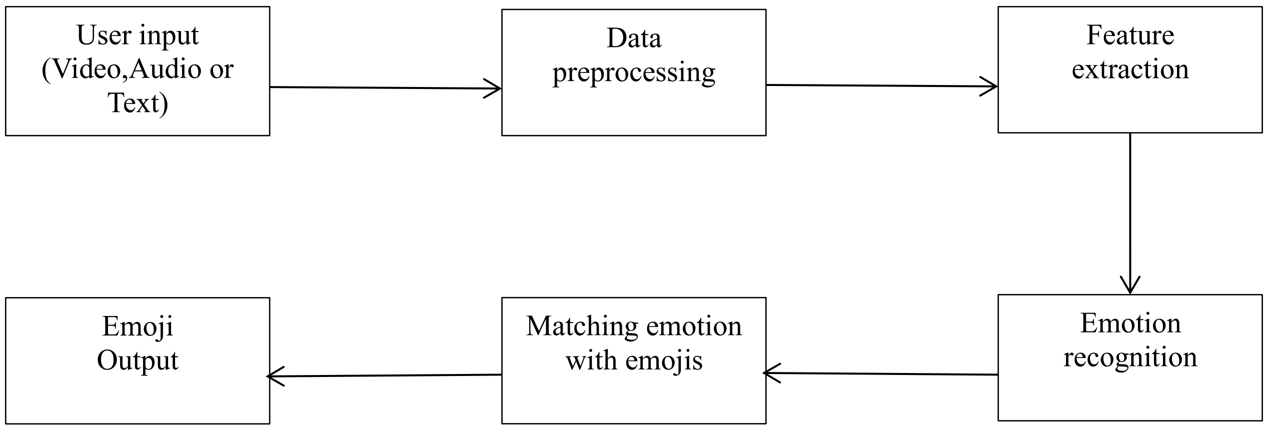


Fig. 4.1 - System architecture

The above figure 4.1 shows that The architecture includes image capture, pre-processing, CNN training model, and emotion-to-emoji mapping. The camera captures the live picture, then image pre-processing suppresses the extracted live input image data and extracts features for subsequent processing. The saved model classifies the collected feature and detects emotion.

4.2 Data Flow Diagram

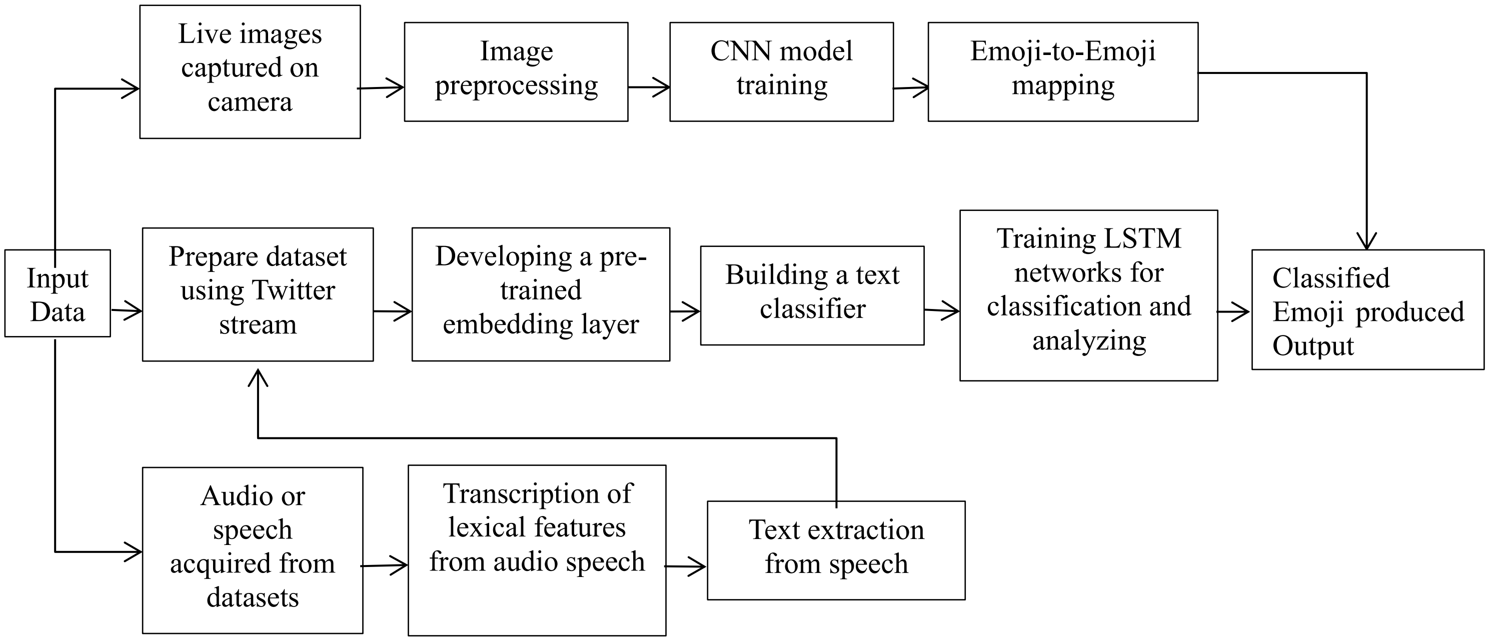


Fig. 4.2 – Data Flow diagram

The above Figure 4.2 shows how the 3 different modules work in tandem with each other to give us the final emoji output. It shows how the data is converted from raw input, its features are extracted and finally classified across the 3 different modules to finally produce an output consisting of a single emoji.

CHAPTER 5

MODULE DESCRIPTION

MODULES USED:

Module 1: Facial Expression To Emoji Converter

Module 2: Text To Emoji Converter

Module 3: Speech To Emoji Converter

5.1 Module 1: Facial Expression To Emoji Converter

The architecture includes image capture, pre-processing, CNN training model, and emotion-to-emoji mapping. The camera captures the live picture, then image pre-processing suppresses the extracted live input image data and extracts features for subsequent processing. The saved model classifies the collected feature and detects emotion. The identified emotion finds the matching emoji from the stored photos. Finally, the output emoji is shown and transmitted instantaneously when an emotion changes. OpenCV defines Haar Cascade face detection. Haar Cascade detects faces. A rectangle box captures the face. Haar Cascade detects faces in each camera frame.

The trained neural network recognises facial expressions and classifies them into one of the seven fundamental emotions. It classifies input images into expressions (angry, sad, happy, surprise, disgust, fear and neutral). Python's Keras package simplifies CNN construction. Computers see pixels. Image pixels frequently relate. It maps user-provided live input image characteristics to emoji. Tkinter forms the GUI module. GUI applications use buttons, sliders, search fields, labels, and textboxes. Python's standard GUI is Tkinter. Open-sTheirce Python framework Streamlit. Python's standard Tk GUI toolkit interface is Tkinter. Python with Tkinter makes GUI apps fastest and easiest.

It is accomplished by capturing the face inside a rectangular box using Haar Cascade and the system is structured in such a way that the live picture is caught through the camera. The system is constructed in such a manner that the live picture can be captured. The steps that are to be followed are:

i. The Haar Cascade approach is applied to each each frame of the camera feed in order to detect faces.

ii. The portion of the image that contains the face is cropped to a resolution of 48 by 48 pixels before being sent as input to the CNN.

iii. After that, the image is preprocessed, which consists of suppressing the live input image data that was retrieved earlier and extracting features in preparation for subsequent processing.

- The identified feeling then looks through the collection of saved emoji for the one that best represents it.
- When a person changes the expression on their face, the emoji that corresponds to that alteration is instantaneously displayed, and it is also shared.
- The captured feature is trained, categorized, and then transmitted to the comparison model, which is where the emotion is detected from the saved model (i.e., there is already trained data there), and the results of the comparison are compared with those of the extracted features.
- This procedure is shown clearly in the below figure 5.1.

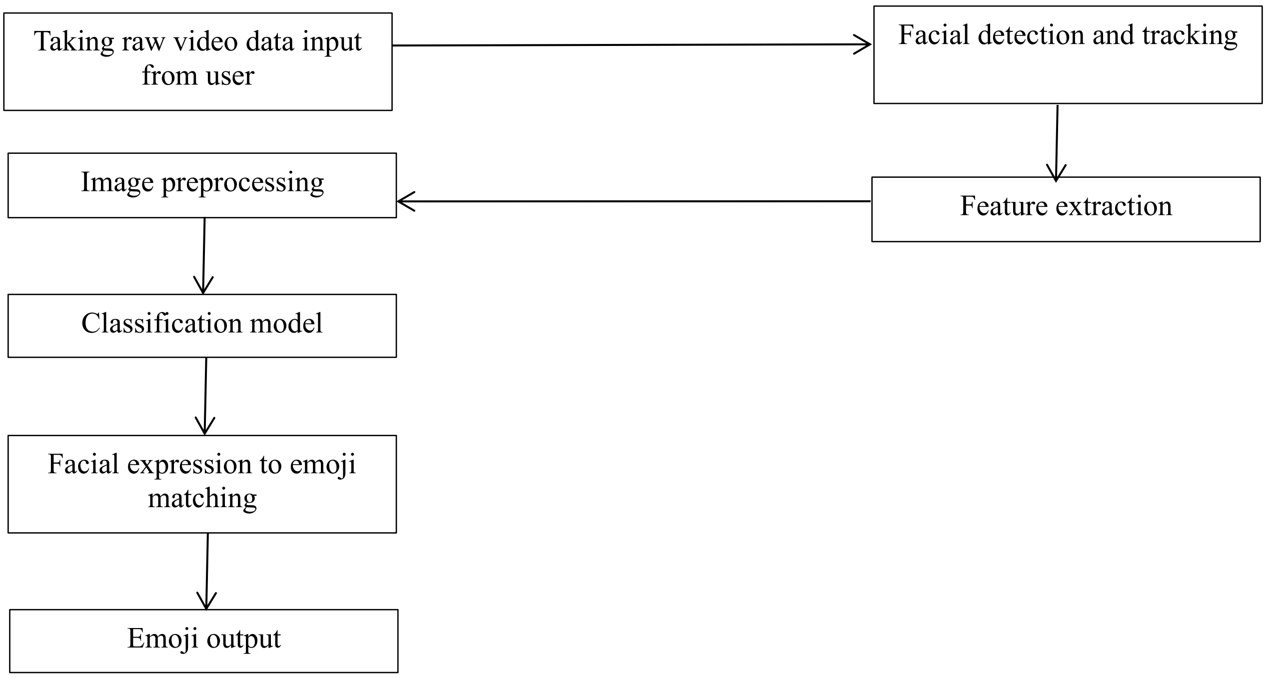


Fig. 5.1-Data flow diagram for module 1

5.2 Module 2: Text To Emoji Converter

This phase assists us in categorizing Their text and provides an emoji in exchange. This means that we will construct a text classifier that, when presented with an English sentence, will make an appropriate emoji prediction. In order to prepare Their dataset, we are going to use the Twitter streaming API. By using this, we gather both the tweets and the emoticons that go along with them. There are two.csv files in the folder containing the sTheirce code that are labelled train emoji.csv and test emoji.csv. These files allow us to download the dataset.The two files, train emoji.csv and test emoji.csv, contain the datasets that we will use to train and test the model that we develop. The layer, known as glove.6B.50d, functions primarily as a pre-trained embedding layer. It is going to be put to use in the process of embedding the words. Emoji Prediction Using Machine Learning is a python file that contains the entirety of Their emoji prediction project's implementation . In light of the fact that we are going to construct the LSTM model. Because of this, gaining an understanding of it will be beneficial. The type of recurrent neural network known as long short-term memory, or LSTM, networks are able to learn order dependency in sequence prediction problems. Classifying, analyzing, and making predictions on the basis of text or time series data are all possible applications for LSTM networks. These steps are clearly shown in the below figure 5.2.

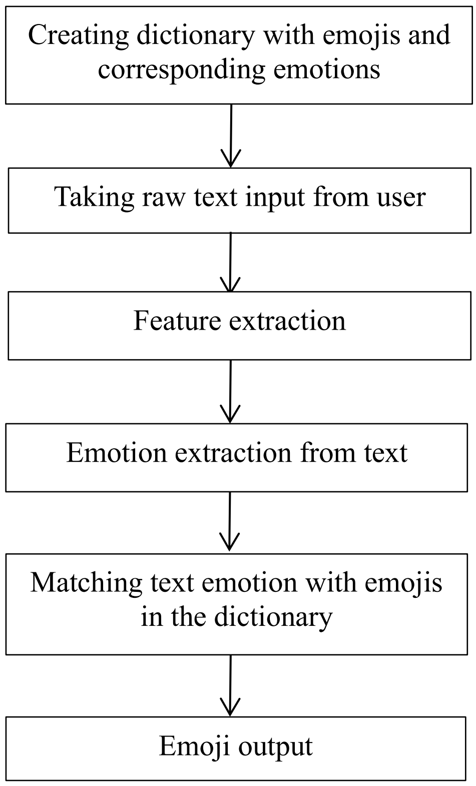


Fig 5.2-Data flow diagram for module 2

5.3 Module 3: Speech To Emoji Converter

Humans naturally express themselves through words. We use emoticons to express Their feelings in emails and text messages since we depend on it so much. In today's digital world of distant communication, detecting and analysing emotions is crucial. Emotions are subjective, making emotion detection difficult. They're not standardised. SER systems analyse and classify speech data to identify emotions.

An interactive voice-based assistant or caller-agent conversation analysis system can be used in many applications. This study analyses the acoustic aspects of recorded speech to discover underlying emotions.Speech has lexical, visual, and auditory aspects (sound properties like pitch, tone, jitter, etc.).

Humans naturally express themselves through words. We use emoticons to express Their feelings in emails and text messages since we depend on it so much. In today's digital world of distant communication, detecting and analysing emotions is crucial. Emotions are subjective, making emotion detection difficult. They're not standardised. SER systems analyse and classify speech data to identify emotions.

An interactive voice-based assistant or caller-agent conversation analysis system can be used in many applications. This study analyses the acoustic aspects of recorded speech to discover underlying emotions.Speech has lexical, visual, and auditory aspects (sound properties like pitch, tone, jitter, etc.).

These time audio, following lexical features requires a transcript and text extraction from speech. Analyzing visual aspects would require access to the video of the discussions, which may not be possible in all cases, but we can analyse acoustic features in real time using simply the audio data. This paper analyses acoustic features. Emotions can be shown in two ways:

1) Classifying emotions as anger, happiness, boredom, etc.
2) Representing emotions with dimensions like Valence (negative to positive), Activation or Energy (low to high), and Dominance (on an active to passive scale)

The dimensional technique is more complex and provides more context for prediction, but it is harder to execute and lacks dimensional audio data. Dimensional representation gives predictive context, yet discrete categorization is simpler and easier to apply. For lack of dimensionally annotated public data, we used discrete categorization in this investigation

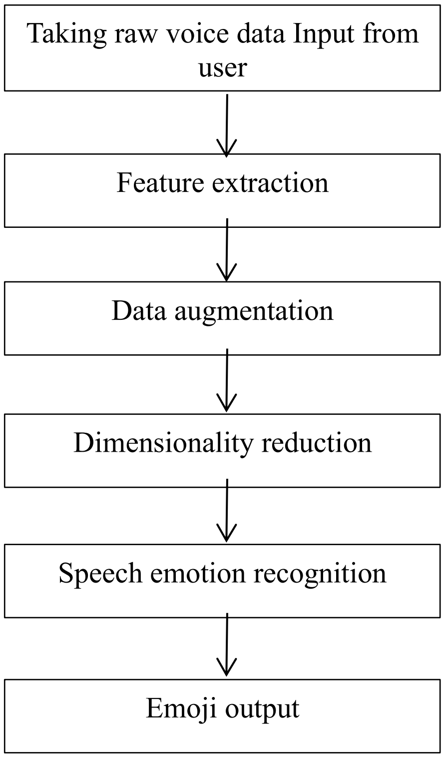


Fig 5.3 - Data Flow diagram for module

CHAPTER 6

SUMMARY

This work aims to provide a worldwide perspective and clues for emoji researchers by conducting a comprehensive review of related studies. This paper provides a concise overview of emoji's history, current state of development, usage patterns, functional qualities, and research areas. Originating as emoticons, emoji now serve both emotional and semantic purposes. Different people, places, and technologies all have an impact on and contribute to the wide range of emoji usage that exists today. It's possible for there to be some ambiguity and miscommunication in many contexts and cultures. This paper examines the state of emoji research from a number of different angles, including communication, computing, behavioral science, marketing, and education, and proposes some new directions for the study of emoji in the future, including explorations of their emotional associations, user preferences, and potential social and technological impacts.

CONCLUSION AND FUTURE WORK

We have demonstrated how the millions of texts on social media that contain emojis may be utilized for pre training models, how the facial expression data set can be used to pretrain the model and also how useful such emoji classification can be in our daily lives. This was accomplished through the usage of these facial expressions and text analysis. We find that the variety of our emoji set is significant for the performance of our method by comparing it to an identical model that was pretrained on a subset of emojis. This was done so that we could draw this conclusion. This basically means that greater the variety of emojis, better is the model. The application of external knowledge has not only improved the accuracy. We have worked on using external knowledge in order to improve our model, which has resulted in improved accuracy while doing tasks involving word expressions similarity and text similarity.

Our future work would involve us increasing the variety of emojis and also improving accuracy there by making our software more usable and compatible with different types of facial expressions and texts.

REFERENCES

[1] "Emotion Recognition Based Emoji Retrieval Using Deep Learning", S.Srivastava, P. Gupta and P. Kumar, 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), 2021, pg. 1182-1186.

[2] "Anon-Emoji: An Optical See-Through Augmented Reality System for Children with Autism Spectrum Disorders to promote Understanding of Facial Expressions and Emotions,"R. Sun, H. Haraldsson, Y. Zhao and S. Belongie, 2019 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), 2019, pg. 448-450.

[3] "Facial Emoji Recognition", N.Swapna Goud, K. Revanth Reddy, G.Alekha and G.S Suchitha, International JTheirnal of Trend in Scientific Research and Development(IJTSRD),Volume:3 Issue:3, March-April 2019, Page No. 1330-1333.

[4] "Real-Time Facial Expression Recognition Based on CNN," K.C. Liu, C.C. Hsu, W.Y. Wang and H.H. Chiang, 2019 International Conference on System Science and Engineering (ICSSE), 2019, pg. 120-123.

[5] "Emojify Create yTheir own emoji with Deep Learning", Payas Doshi, Priyanshi Sethi, Pulkit Sharma, Mahaveer Jain, International Research JTheirnal of Engineering and Technology (IRJET), Volume: 08 Issue: 11 , Nov 2021.Page No. 1014-1024.

[6] "Exploiting Deep Neural Networks for Tweet-based Emoji Prediction",Andrei Catalin Coman1 , Giacomo Zara , Yaroslav Nechaev , Gianni Barlacchi , and Alessandro Moschit, University of Trento, Trento, Italy.

[7] "Transformation of Facial Expression into corresponding Emoticons", Ankur Ankit, Dhananjay Narayan, Alok Kumar International JTheirnal of Engineering and Advanced Technology (IJEAT). Volume-8 Issue-5, June 2019

[8] "Mapping of human facial expressions to emojis using Deep learning", Parth Vishe , Pune Institute of Computer Technology, Pune, Maharashtra, India. May 2022, Volume 9, Issue 5 .

[9] "Emojify: Emoji Prediction from Sentence", Chen Huang, Xueying (Shirley) Xie, Boyu (Bill) Zhang, Stanford University.

[10] "EMOJIFY-CREATE YTHEIR OWN EMOJIS WITH DEEP LEARNING" Sagar Chilivery, Sandeep Pukale, Yashraj Sonawane Vasantdada Patil Pratishthan's College Of