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Twitter Emotion Detection and Recommendation of Motivational Video

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ABSTRACT

Natural language processing faces a number of difficult & growing difficulties, one of which is the identification & interpretation of emotional cues in text (NLP). Textual data can be used to infer a person's emotional state, but there is also research being done on facial, video, & audio data to do the same thing. Many domains, including neuroscience, data mining, psychology, HCI, e-learning, information filtering systems, & cognitive science, can benefit from the study of emotions. Social media has developed as a new venue for people to communicate their opinions and perspectives on a variety of issues and topics with their friends and family members and other users. Texts, images, audio/video communications, & social media posts allow us to express our ideas, feelings, & positions on various social & political problems. Though various modes of communication are available, text remains the most prevalent form of communication in a social network. Research in this subject aims to identify & evaluate both the sentiment & emotion exhibited in tweets by analyzing the language. Some recent tweets & replies were gathered and a dataset containing text & user, emotional & sentiment information was constructed. Emotions are taken into account while recommending video content in the proposed system.

KEYWORDS: Emotiondetection, Emotion Models, Sentiment, Text, Psychology

INTRODUCTION

It is possible to automate or semi-automate the recognition of human emotion by using a computer-based system or by relying solely on personal abilities and interpretations of interpersonal interaction in the process of emotion recognition. Automated emotion recognition has been created using a variety of methods, including human-computer interface (HCI)[1]. Siri and Cortana, two of the most popular intelligent assistants, employ a wide range of idiosyncrasies in their interactions with humans. Recognizing emotions before executing activities can boost HCI even more. Accurately deciphering human feelings is a time-consuming endeavor because of their variety and ambiguity. Some feelings are conveyed in various ways, and some feelings are represented in the same way by more than one emotion. Emotions can be influenced by a person's personality, gender, geography, race, and culture, as well as many other factors. Even for another human, it can be difficult to discern a person's true emotion from written words, spoken words, or facial expressions. It's easy to imagine the problem's complexity when it comes to computer-assisted emotion recognition. Emotion recognition from a variety of inputs has been the focus of numerous studies (e.g., text, image, audio, video, etc.). Emotion recognition can be conducted using a variety of types of input, including speech, text, and video/image [2]. Several systems already exist that use this mix of information to recognize emotions [3]. The problem is that in many circumstances, you won't be able to access all of the information you need. Amazon, for example, may use text review data to do emotion recognition; contact centers may employ audio speech recognition to detect emotions; and security cameras must rely solely on visual information to perform emotion recognition.

EVOLUTION OF EMOTION

Charles Darwin asserted in 1872, following a series of psychological tests including recordings of animal & human facial expressions under a variety of conditions, that animals and humans exhibit similar emotional expressions and behaviors under similar conditions [4]. It was also influenced by the times and the surroundings in which he lived. According to his ideas, the realization of emotions in humans and other animals takes time. He went into great length regarding the broad principles of emotions, the ways in which emotions are expressed in both humans and animals, and the causes and effects of all possible emotions, including anxiety, grief, dejection, despair, joy, love, & devotion. Some emotional expressions, according to Darwin, can be found in humans around the world. It was also suggested that animals of the same species react to a circumstance in the same way. Experiments conducted by him have shown that even in species that are not closely related, there are some emotions that have comparable facial expressions. Before then, there was some sort of philosophical & spiritual categorization of emotions [5].

Emotional research has its roots in philosophical and psychological theories. Emotions or the ways in which they are expressed, according to Darwin, have biological roots. "Brain mechanisms that are outputs of functional aspects of neuronal systems"[6] were later used to characterize emotions. Figure 1 depicts the development of emotion in several fields of study over time. Different human emotions were determined to be realized at various stages of human existence and in various eras according to the evolution theory. Researchers from a wide range of professions have been delving into human emotions and developing numerous models to encompass all of the conceivable human emotions that can be expressed through the mind and body.

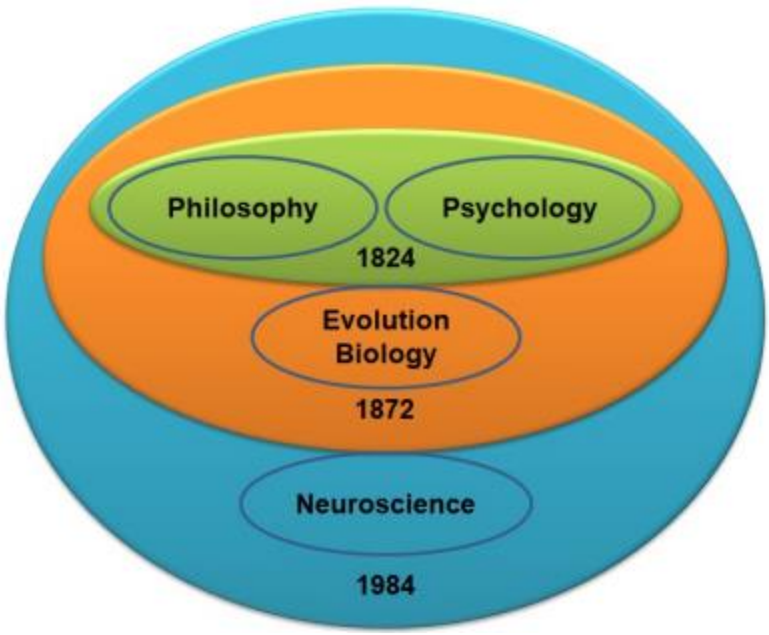

Figure 1: Evolution of Emotion in Various Fields

EMOTION MODELS

Due to the fact that individuals are capable of identifying and naming their own emotions, the scientific community has come to approach them differently. People, according to psychologists, have internal processes for a restricted set of emotions (most commonly happiness, sadness, anger and disgust) that can be judged in a straightforward and objective manner when engaged. In psychology, there are three main techniques to expressing emotions: [7]

Categorical approach: This approach to emotion categorizes and classifies emotions into separate & globally recognized categories [8]. Paul Ekman[9] categorizes human emotions into six main categories: happiness, fear, sadness, surprise, disgust, & anger. These six basic emotions are all independent of one another.

In the concept given by Robert Plutchik[10], acceptance / trust & anticipation were two of the eight primary feelings. Surprise against anticipation, joy versus sadness, rage versus fear, & trust versus contempt are all examples of opposite emotions. According to Plutchik, there are variable degrees of intensity for each emotion as a consequence of the experiencer's perception of events.

The "fundamental emotions" comparison proposed by Ekman[9] diverged from the paradigm of Orthony, Clore, & Collins (OCC). They agreed, however, that the intensity of an individual's perception of events and emotions was a factor in the emergence of emotions. For the first time, there are now more than two dozen distinct emotions that can be categorized into 22. Ekman's basic emotions were expanded to include 16 additional emotions and an even wider range of emotions such as envy; relief; appreciation; self-reproach; shame; repentance; pity; admiration; disappointment; grief

Dimensional approach: Emotions, rather than being considered separate entities, are seen as intertwined in this view. Emotions are linked to certain events and can range from mild to severe, which is why they're depicted in various dimensions spaces. Multi-dimensional models for emotional representation are examined in greater detail in this article.

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There are two dimensions to Russell's circumplex model [12]. It is important to note that emotions do not exist in isolation; rather, they are divided into two distinct categories: Arousal (Activation & Deactivation) and Valence (Pleasantness and Unpleasantness). Figure 2 depicts Russell's circumplex model of the emotional response..

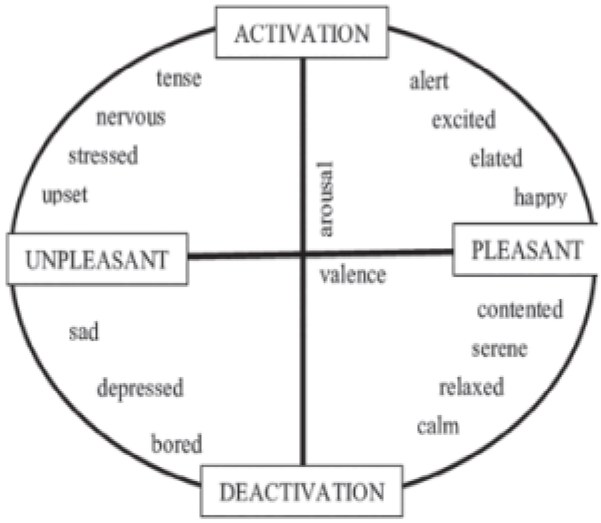

Figure 2: Circumplex model by Russell.

Using a two-dimensional model, Plutchik's wheel of emotions is depicted in figure 3 by a wheel of emotions. The inner core emotions are versions of the eight basic emotions, followed by the 8 basic emotions in the outermost sections of the wheel, and lastly combinations of the primary emotions in the outermost areas of the concentric circle. Based on where you place your finger on the wheel, you may see how your emotions are linked together.

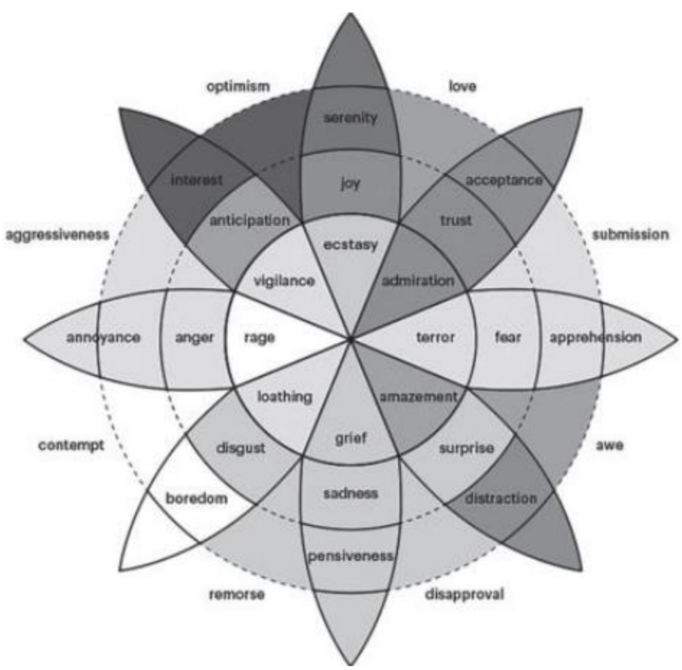

Figure 3: Plutchik's Wheel of emotions

Emotions are categorized into three dimensions by Russell &Mehrabian, namely, pleasantness, arousal, & potency (or dominance). Arousal (Activation and Deactivation), Valence (Pleasantness & Unpleasantness), & Dominance Power (the

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degree that an experienced has been in control of their emotions) are the three dimensions of 2D depiction of emotions. Three-dimensional emotional space is depicted in Figure 4.

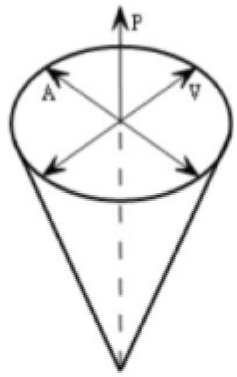

Figure 4: 3D Emotion Space (Valence, Arousal, & Power)

"Primary" emotions include "joy," "anger," "fear," "love," & "surprise," and "secondary" & "tertiary," according to Parrot [13]. Emotions utilized in the Parrot Emotion Taxonomy are depicted in Table 1.

Table 1: Parrot's Emotion Taxonomy

Primary emotions	Secondary emotions	Tertiary emotions
Love	Affection	Caring, sentimentality, adoration, fondness, compassion, tenderness, love, attraction, affection, liking.
	Lust	Desire, arousal, passion, Infatuation, lust.
Joy	Cheerfulness	Euphoria, satisfaction, gladness, ,bliss, happiness, Jubilation, delight, elation, enjoyment, joviality, joy, Amusement ecstasy, jolliness, gaiety, glee, cheerfulness.
	Zest	Thrill, excitement, enthusiasm, exhilaration. zeal, zest.
	Contentment	Pleasure, Contentment.
	Pride	Triumph, Pride.
	Optimism	Optimism, hope, Eagerness.
Surprise	Surprise	Astonishment, surprise, amazement.
	Irritation	Agitation, annoyance, irritation, grouchiness aggravation,
Sadness	Sadness	Gloom, grief, melancholy despair, glumness, misery, unhappiness, hopelessness, sadness, depression, sorrow, woe,
	Disappointment	Dismay, displeasure , disappointment
	Shame	Regret, shame, remorse, guilt
Anger	Exasperation	Frustration, exasperation,
	Rage	Bitterness, loathing, wrath, dislike, hostility, spite, resentment rage, ferocity, hate, scorn, fury, anger, vengefulness, outrage.
	Disgust	Contempt, revulsion, disgust.
	Suffering	Hurt, agony, anguish suffering,

Appraisal based approach: In this way, the Dimensional Model can be considered as an extension of this technique. Componential emotion models based on appraisal theory are included. When an event occurs, it can produce a wide range of feelings in distinct people at different periods, according to appraisal theory. Changes in cognition, expressions, physiology and motivation, as well as reactions and sentiments [7] can be observed by the emotions. Emotional states in the categorical

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approach are limited to a small number of different types, making it difficult to deal with complicated emotional situations or mixed emotions. However, the dimensional method does not encompass all of the basic emotions. So the componential model [7] could be applied in accordance with different emotional states due to the appraisal pattern's varying variability.

EMOTION DETECTION

Research on the extraction of emotions from various sorts of social network components has been going on for quite some time. Contents submitted by people on social networking sites have been evaluated to identify the underlying feelings. Emotion has been detected from multimodal data using a variety of methods, including voice tone, speech, facial expressions, gestures, EEG signals, other biosignals, and texts[14]. Most studies on emotion recognition, on the other hand, focus on a single type of information. Faces and gestures captured from video were utilized to extract emotions in[16], although audio inputs including speech tone and frequency were employed to help detect emotions in[15]. However, as previously said, this study will focus on the recognition of emotions and sentiments from text.

EMOTION & SENTIMENT

Detecting 'emotion' from text is a more difficult task than detecting'sentiment.' 'Emotion' and'sentiment,' though sometimes used interchangeably, refer to two distinct things in text analysis. The Oxford Dictionary defines "emotion" as "a powerful sensation originating from one's circumstances, mood, or interactions with others," & "sentiment" is "a view or opinion that is held or expressed. ". Emotions and sentiments are defined by the Cambridge Dictionary as "a strong sensation such as love or rage, or strong feelings in general," while the term "sentiment" is defined as "a concept, opinion, or idea that is formed by a feeling, or a way of thinking, about a situation." 'Emotion,' according to the American Psychological Association, is "a complex pattern of changes, involving physiological arousal, sensations... cognitive processes and behavioral reactions, made in response to an event thought to be personally relevant." For the most part, "sentiment" is a term that refers to an emotional response[17]. Examples of emotions are "Happiness," "Anger," "Love," & "Positive," "Negative," respectively, which are examples of matching sentiments. As a result, the term "emotion" is used more frequently than the phrase "sentiment" because it is a more comprehensive meaning of "feeling."

EMOTION & SENTIMENT IN TEXT

Personality & conduct are reflected in the complexity and multidimensionality of human emotion. People communicate their thoughts and feelings about a variety of subjects in their daily lives, including events, people, the environment, and even the tiniest details of their surroundings. They employ a variety of strategies to communicate their feelings. Speech and facial expressions are the most popular ways to communicate one's feelings to others. As a result of the widespread use of social media, people are now more frequently and openly documenting & expressing their feelings. Though new technology has made it possible for people to communicate with each other through audio and video, text remains the most frequent mode of communication on social networking sites. Social media posts are a way for people to express their feelings and thoughts (e.g. status, comments, blogs, microblogs). Social network posts have been employed in recent textual emotion analysis studies because of the large number of participants & posts. Facebook, Twitter, Instagram, and YouTube are just a few of the many social networks that more than 2.46 billion people use. It's difficult to decipher the meaning of these pieces and the emotions they express through their language and semantics. It's long been a promising study issue, and a lot of work has been put into developing a perfect automated system that can correctly identify human emotions in texts.

EMOTION & SENTIMENT IN TWITTER TEXTS

Sentiment analysis[19] employing micro-blogs or tweets is relatively young compared to the field of emotion identification from Twitter tweets. After launching in 2006 with no constraints on what users could publish or how often they could post, Twitter quickly became a hugely popular social networking platform. Tweets are short posts limited to 140 characters in length. Because of it's character limit and the fact that people of various ages use Twitter to communicate their views on a wide range of topics, Twitter data is a popular choice for text analysis jobs. It may be possible to get a sense of a person's mental condition by extracting text from Twitter and examining tweets they have sent. Automatic emotion recognition from tweets is difficult due to the complexities of Twitter data & wide range of human emotions. However, determining a person's emotional state is a pretty simple task. Emotion & sentiment were detected and analyzed on the Twitter network in this study. Tweets and answers were analyzed to build an emotional network based on the emotions and sentiments expressed. People with sway over a wide range of emotions and sentiments were identified using the emotion network. Ultimately, a trust network based on the emotional similarities & influences was constructed. An example of a tweet and a variety of twitter

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answers are shown in Figure 5. An problem was brought up in the tweet, and some individuals agreed with the author like the second and third comments. Like the fourth comment, some people objected to the tweet and expressed their disdain or rage. In some cases, like the tweet's first response, reasoning was used to respond to the tweet, while in others, no emotion was shown at all.

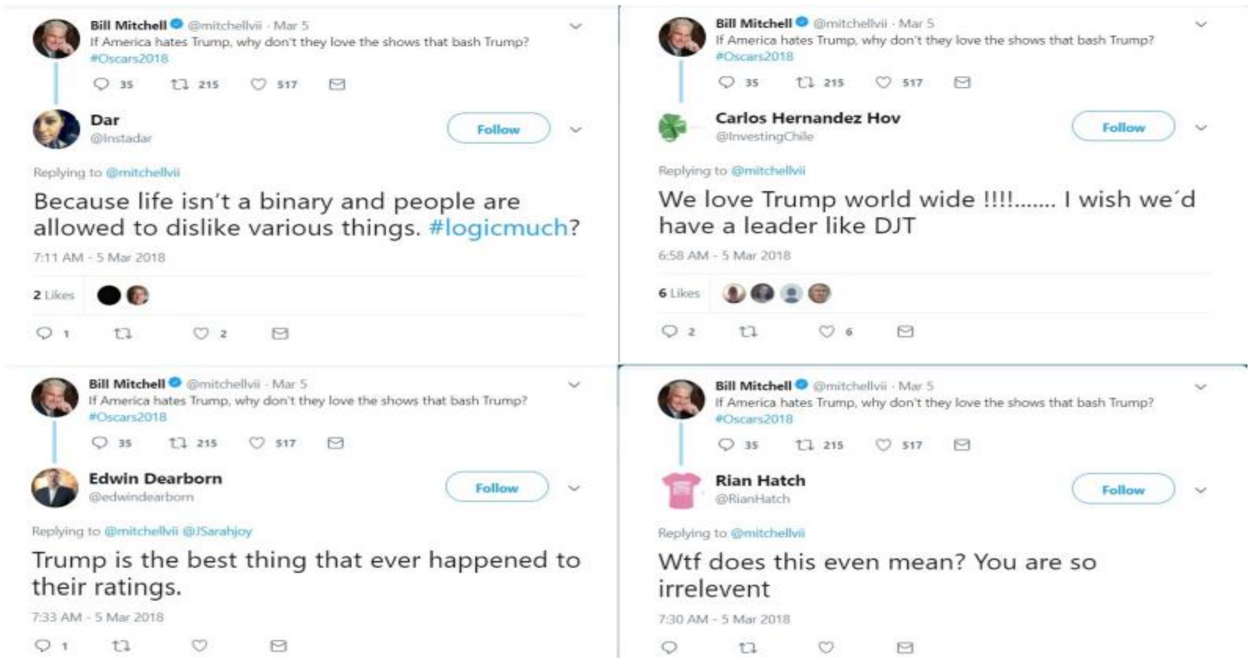

Figure 5: Sample Tweet & Replies.

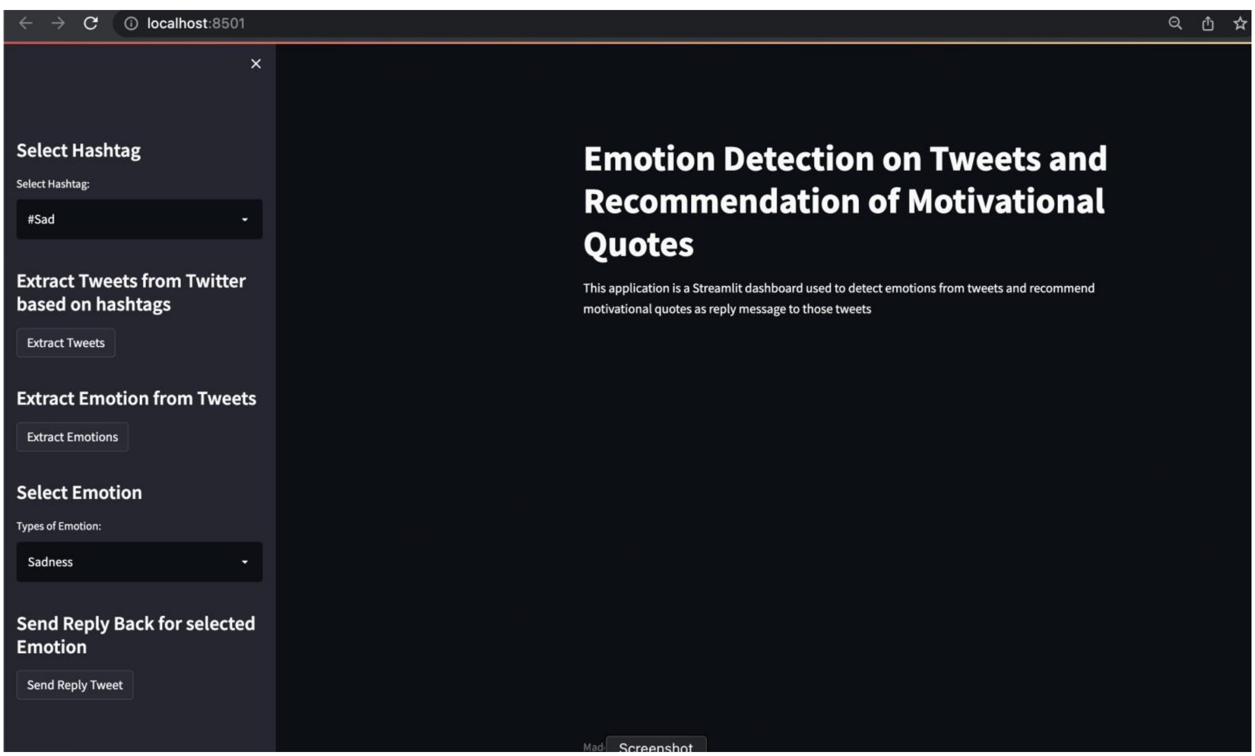

Figure 6: Entire_Dashboard

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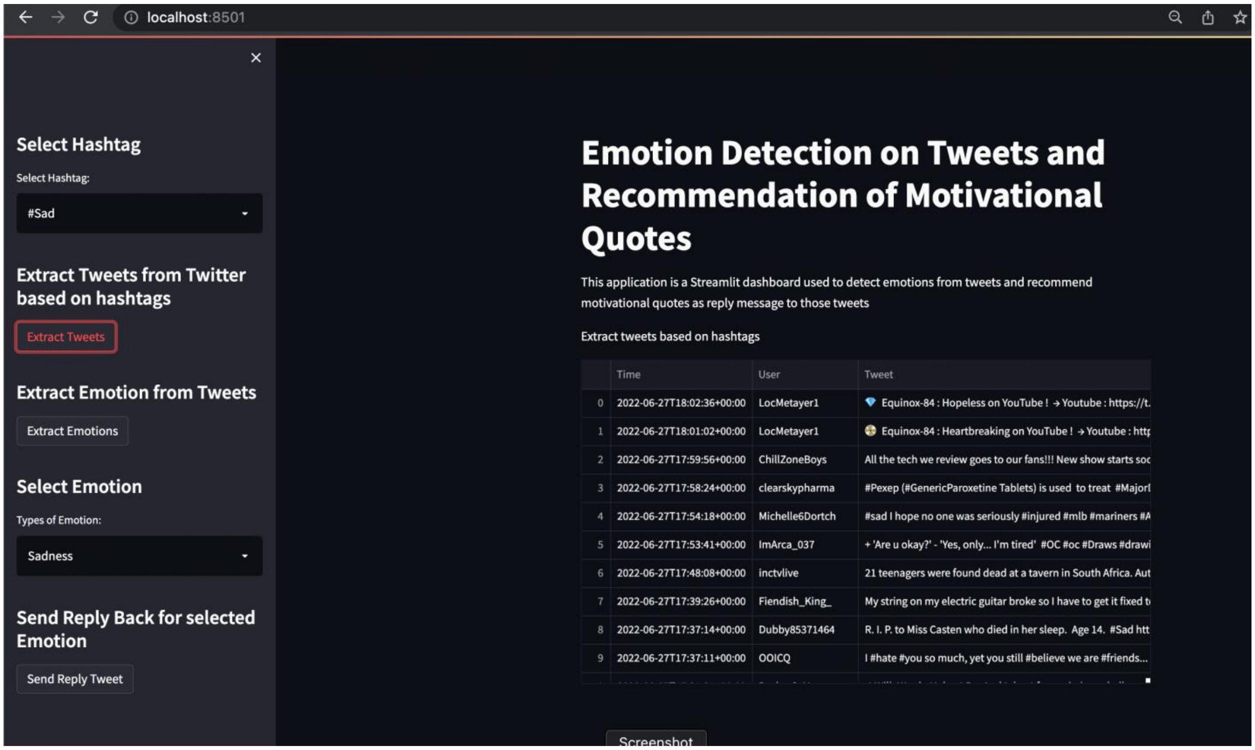

Figure 7: Extract_Tweets

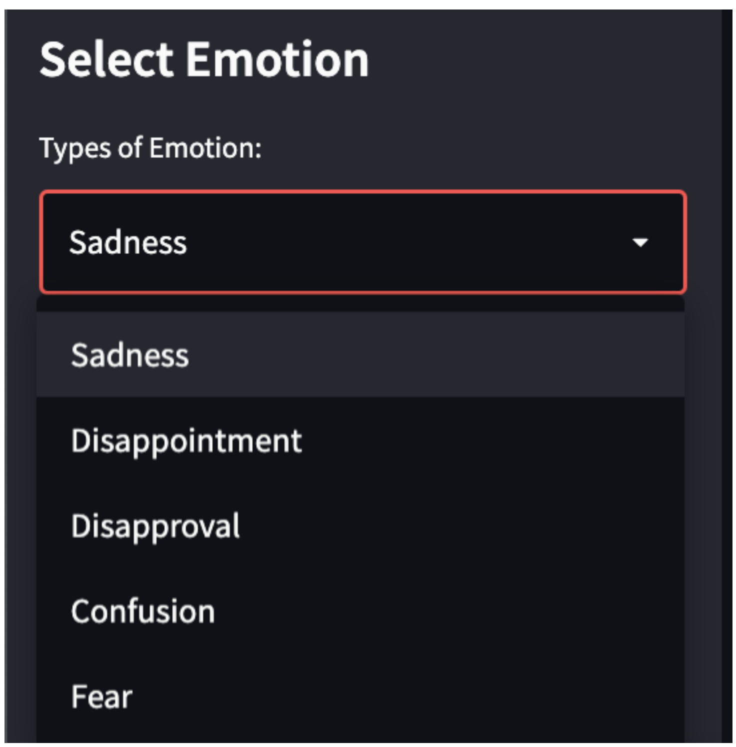

Figure 8: Types_of_Emotions

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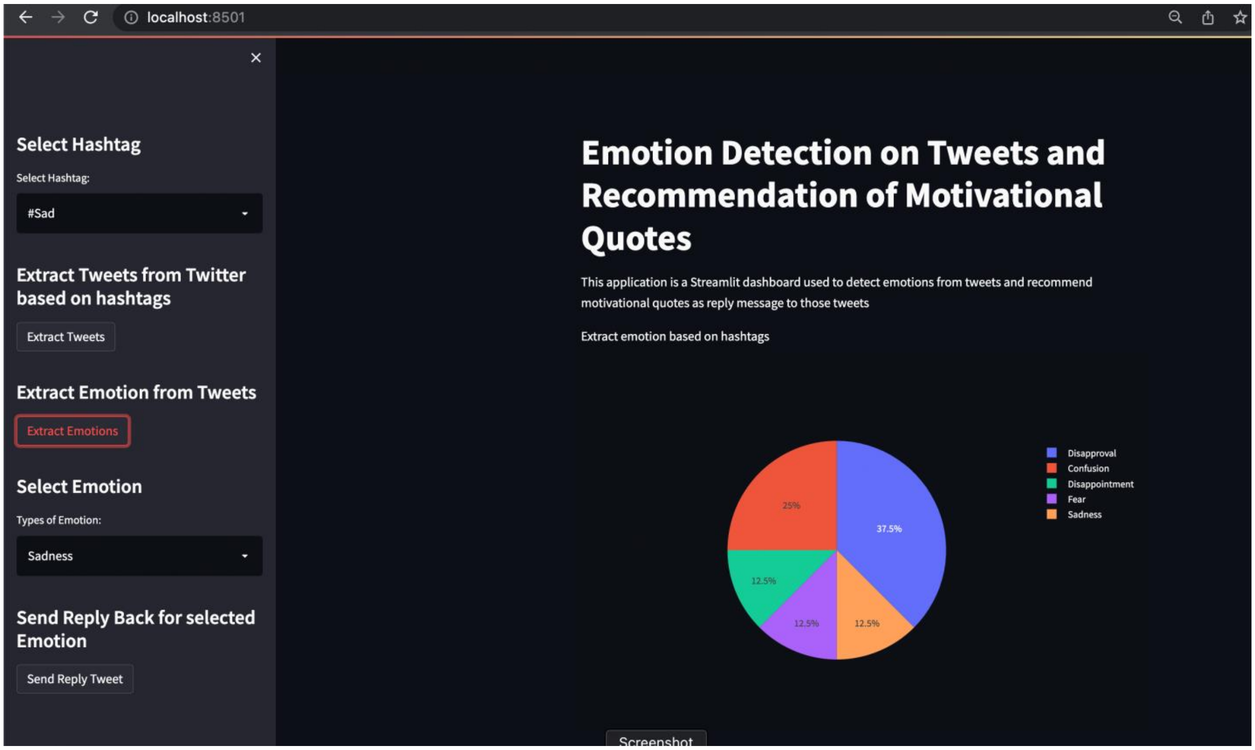

Figure 9: Emotion_Detection_from_tweets

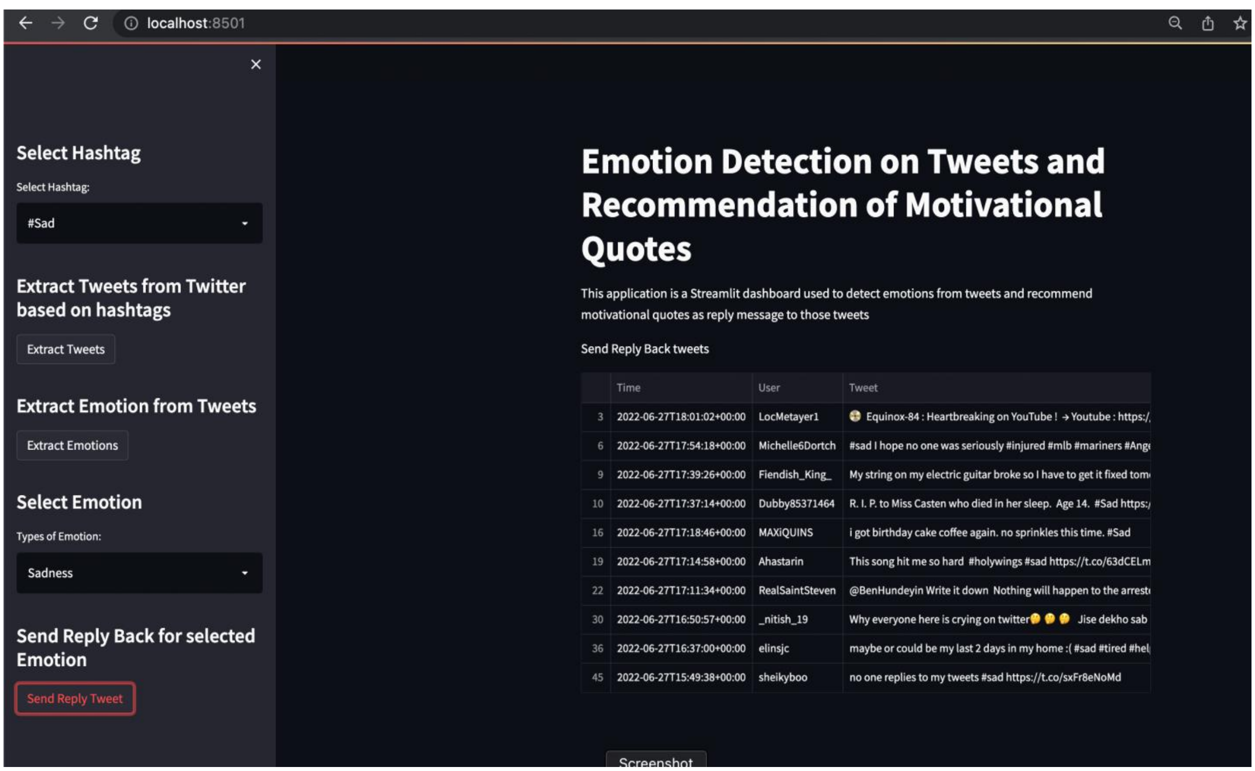

Figure 10: Send_Reply_Back

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PROPOSED SYSTEM

A real-time recommendation system based on emotions is what we are proposing. The user's personal assistant is provided by this system. Face features are extracted in real-time using video inputs from users because it is a feature extraction & recommendation system. Algorithms such as LBP and Haar Cascade are used to determine the user's emotional state by analyzing their face features. In order to produce facial expressions, muscles in the face are frequently moved in a manner & pattern that can alter the position and shape of facial features such as the eyes & eyelids, the nose, the lips, cheek muscles. It's possible to utilize this system as a personal assistant just for fun. What sets our approach apart from others is that it categorizes recommendations based on personal preferences & age categories. Gender and age can influence one's personal preferences. Emotions , age & gender are taken into account when recommending videos to users.

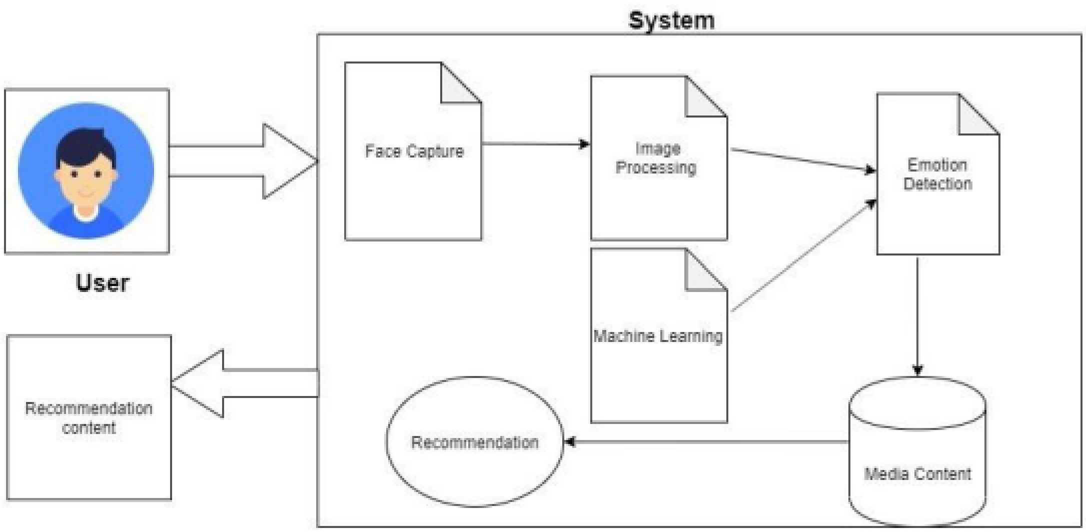

Figure 11: Architecture of the System

METHODOLOGY

A. Face Acquisition

Haar cascade classifiers, LBPH [21], &OpenCV are used for face detection. Faces or body components can be identified using the Haar cascade classifier. Training it to recognise any object in an image is simple and easy. Every area of the input image is processed by a set of classifiers known as Haar features. To begin, gather all of the Haar attributes. A section of an image or video frame can be targeted for analysis, after which algorithms will add up the pixel intensities to produce positive & negative images. After each region has been processed, the difference between sums is discovered in order to extract characteristics. When it comes to the classifier's accuracy, it's the Haar characteristics that shine. Hetograms are constructed by looking at nine pixels at a time. Radius, Neighbors, Grid X, Grid Y [22] are some of the options. The face is detected utilizing coordinates.

B. Feature Extraction

As soon as a face is discovered, a method for locating specific feature points on the face is initiated. Eyes, brows, lips, cheeks, etc. are the primary facial features. This data is used to track the movement of all of these feature points. Scaling, translation, & rotations are used to normalize feature extraction. As a result, maximum extraction efficiency is ensured. The image's points are repositioned and their alignment is verified during translation. A fixed distance from the camera and a fixed size are achieved using scaling. These are not present in every frame of video or image in the dataset. Only when absolutely necessary is the image rotated. Rotations and facial expressions are recorded in cases where the head is inclined to one side or features are difficult to discern.

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C. Age & Gender Detection

There are three steps involved in automatically determining a person's age from an image captured using a webcam.
Extraction of the face region and use of the age detection algorithm to determine the person's age
Haar cascades are utilized in the first stage to identify a person's face. To keep things simple, we just look at one face at a time. If you put your face into the system, it can generate bounding boxes for your face. Deep learning-based face detection is the favored method for achieving the most accurate results.
The following age ranges have been employed: (0-2, 4-6, 8-12, 15-20, 25-32, 38-43, 48-53, 60-100)
These are not contiguous because age is primarily determined by appearance. These subcategories, then, produce the best outcomes. First, a false positive face in the frame is filtered out of the frame in order to determine age from a video stream. A close-up of the face to the camera improves accuracy in age classification. A convenience function that accepts a frame, locates a face, & forecasts age is employed. Detection & confidence filtering are achieved by sending blobs through a CNN. Region coordinates are extracted for faces that meet the minimum level of confidence and age is projected using the age ranges listed above. We utilized the Adience dataset & following algorithm to determine gender.

Algorithm Gender Detection

Input: labeled supervised data for gender detection G and unlabeled data for recognition R.
Output: Predict the data, test labeled data T using Machine Learning Model M.
Steps: -

1. Label the data and divide the mixed labeled data for the detection of gender G.
2. Normalize the data for R.
3. Divide G and R separately.
4. Create model MG and MR for Data G and Data R resp
5. For each Mi do
6. Pre-process the data
7. For ("male", "female") do
8. Predict the real detected face and categorize either male or female
9. End for
10. End For
11. Retur

D. Emotion Detection
Detecting emotions is the system's most crucial function. As a result of the above-mentioned outcomes, the user's emotional state can be determined.
It is possible to detect a range of emotions:
• Happy • Angry • Sad • Fearful • Disgusted • Neutral • Surprised
As a result of these findings, the trained model attempts to forecast the user's emotional state.

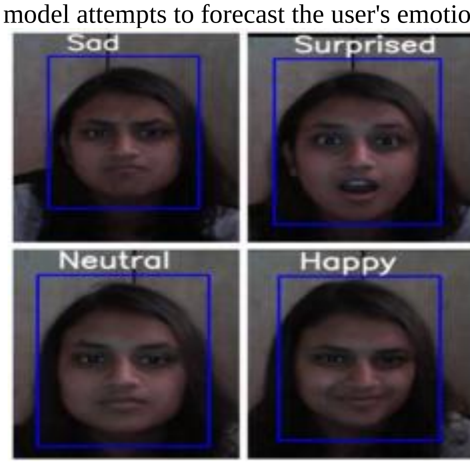

Figure 12: Emotion Detection

E. Recommendation

The focus of the content-based strategy is on the people or things being suggested. Emotion-based recommendations require extra information such as age and gender, which we may obtain through our system. Content-based approaches are used to develop a model, watch the user's interactions with an item, and then build a model from that data. It is possible to reconstruct the user's interactions with an object by using a collaborative model. Based on this model the user is then presented with suggestions. Using content-based approaches, a model is given material to describe a user's behavior. This model may have a low variance and a large bias. Item modeling, optimization, and computation are all involved if our categorization system is based on user features. The likelihood that a user will enjoy a specific item is taken into account in this situation. Data from a large number of users is used to train the model. Using more robust methods will not improve personalization in this case. Also known as "user-centered" design is when the user performs the modeling & computation for a given feature. The likelihood of a user liking each item is taken into account here. That implies it's a lot more tailored than before.

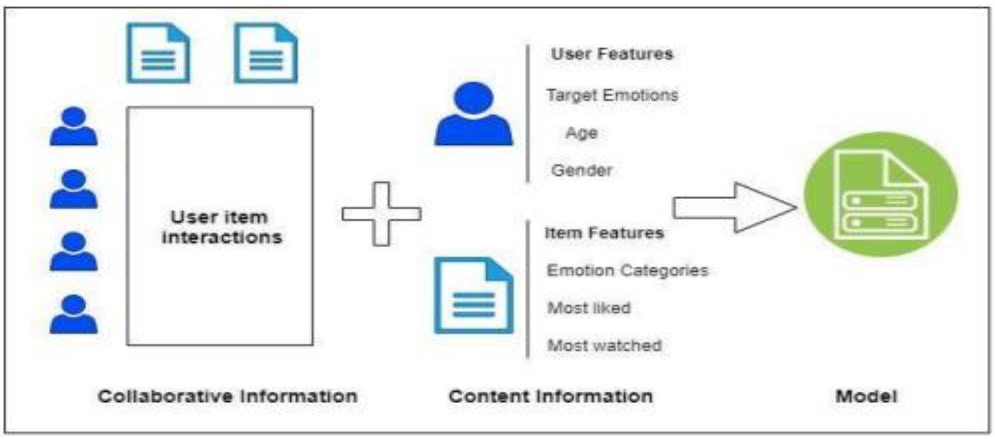

Figure 13: Content-based recommendation

F. Database Connectivity

Access to a database is required in order to protect user data & program. Authentication info for users is stored in Python Sqlite3. With a username/email address & password, users can access the system's features. This is the only data that is kept in the database.

G. Django

An open-source web application framework called Django is available for download and use. It takes less time to get an application up and running with Python &Django. The MVT (ModelView-Template) architecture is the foundation of this system [23].

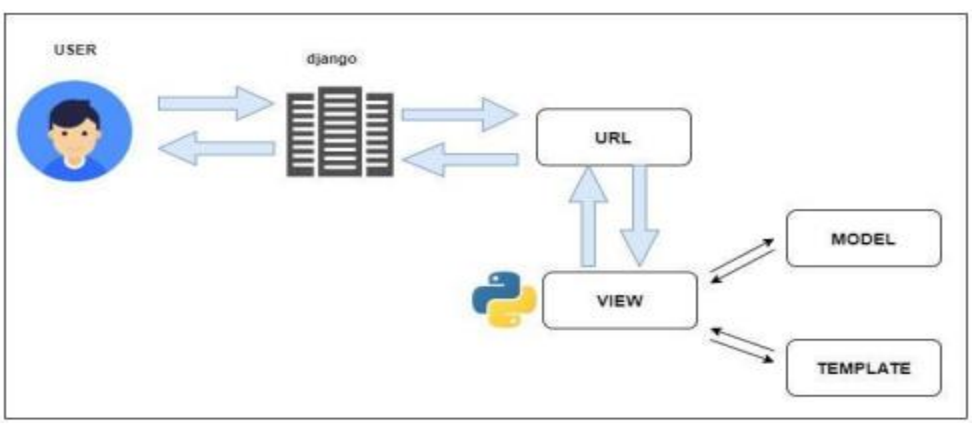

Figure 14: Django MVT Architecture

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CONCLUSION

Emotional expressions are the primary mode of communication in interpersonal relationships. A pleasant, negative, or neutral emotion can all be used to describe this state of mind. Due to the fact that individuals are capable of identifying & naming their own emotions, the scientific community has come to approach them differently. For some reason, it seems difficult to analyze emotions from text documents since expressions in texts don't usually employ emotion-related terms, but rather result from a knowledge of concepts & their interactions. Django is the framework of choice because the system is a web application. Video recommendations are made using a content-based approach. The system will suggest videos based on the user's emotional state. Additionally, the user's gender & age are taken into account while creating a custom experience. The internet recommends videos that are more likely to elicit a desired emotion, are the most popular, or have received the greatest interaction from other users. Music videos, motivational speeches, quotes, movies, cartoons, humor, action, & lifestyle are all included in the many video categories.

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