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Navigating Mental Health: Emotion and Personality-Based Prediction System

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Abstract
Easily available, customized and efficient mental health support services require immediate focus as seen by the rise in issues related to mental health. People looking for quick measures face challenges due to the difficult, subjective or lacking nature of standard procedures for monitoring for mental health issues. Awareness of an individual's mental condition requires an awareness of their mental health and personality features but these elements are rarely integrated into a coherent framework for continuous monitoring and management. This study fills this gap by using cutting-edge machine learning algorithms to forecast mental health disorders based on personality trait analysis and real-time emotion recognition. With actual time capture of images using OpenCV the system uses a CNN to reliably recognize emotions including "Anger," "Contempt," "Disgust," "Fear," "Happy," "Neutral," "Sad" and "Surprised." It achieves an impressive 94% accuracy in training and 100% testing accuracy. Furthermore, personality qualities such as Reliable, Extraverted, Serious, Lively and Responsible are predicted using Logistic Regression. By combining these predictions, the system evaluates the person's mental health and offers useful information such as specific mental health advice and suggestions for relaxing or inspirational videos selected through the YouTube API. Real-time heath detection and personalized treatments are made possible by an interface that guarantees accessibility and promptness.

Keywords: *CNN, Emotion Detection, Mental Health Prediction, Real-Time Interface, Video Recommendation and YouTube API.*

1. Introduction
One of the most important worldwide health issues of the twenty-first century is mental health which has widespread effects on people, families and society at large [1]. Physical health issues frequently overtake the significance of mental health yet mental health is just as vital to an individual's overall wellness and enjoyment of life. Millions of people worldwide suffer from mental health issues like stress, anxiety and depression which affect interpersonal relationships, emotional control and cognitive performance [2]. Although the influence of mental health on social well-being, education and productivity has been acknowledged in recent years stigma and misunderstandings still keep many people from getting the care they need. Since the mentally, emotional and behavioral features of mental health issues often combine it can be difficult to offer people in need of help easily feasible and effective remedies. In order to lessen the long-term impact of mental health illnesses, early detection, individualized care and prompt interventions are essential. The mental health situation in India is especially difficult because of lack of information, cultural stigma and restricted access to resources. One in seven Indians suffers from a mental health condition with anxiety and sadness being the most common in accordance with the National Mental Health Survey [3] (2015–16). However, there are still insufficient income for mental health care and there are few skilled professionals available especially in rural areas. A lack of medical care and encouragement results from the frequent confusion or misdiagnosis of mental

medical conditions. An individual's mental health is greatly affected by their personality features in addition to their mental health. A person's personality impacts how they view and react to stress, contribute with others and deal with limitations in life. Particularly characteristics that are closely associated with mental health include commitment, openness and emotional stability. However emotional control and mental health can be adversely affected by personality disorders including narcissistic, antisocial and borderline personality disorders [4]. Resilience to emotional disorders is also influenced by personality qualities extraverted people are frequently better able to handle stress than introverted people. A better knowledge of personality features can offer important insights into an individual's emotional state, presenting chances for more individualized and successful mental health therapies according to research in psychiatry and psychology. There has never been a greater need for novel approaches to mental wellness treatment [5]. Despite their effectiveness traditional techniques of evaluation and treatment can have drawbacks in terms of timeliness, accessibility and adaptation. Technological developments especially in the areas of neural networks and algorithms for learning have the ability to completely transform mental health services by providing personalized, data-driven and real-time solutions. Large-scale data analysis using machine learning techniques can identify emotional and behavioral patterns allowing for the early detection of mental health problems and more precise forecasting of effects on mental health.

2. Literature Survey

The easy creation of systems that use various machine learning algorithms to identify and analyze emotional states is the main focus of current work within the field of mental health prediction and analysis. One important aspect is emotion detection especially through facial expressions. Convolutional Neural Networks (CNNs) alongside various deep learning techniques are used by computers to analyze photos or videos and pinpoint particular emotional states. These systems are generally implemented utilizing real-time video capturing technology enabling fast emotion recognition which is vital for purposes such as virtual health personal assistants, real-time feedback and personalized therapies. Mellouk et al. examines current research on deep learning-based automatic face emotion identification [6]. It contrasts suggested approaches and outcomes and highlights investments, architecture and databases used. The objective is to help researchers advance this area by offering suggestions for bettering human-machine interfaces, safety and health. Jain et al. introduces a novel method for DNN based facial emotion identification [7]. The model uses deep residual blocks and convolution layers to categorize photos into six emotional facial groups. Using samples like CK+ and JAFFE the model improves accuracy over earlier models and outperforms existing emotion identification techniques. Jaiswal et al. a convolutional neural network (CNN) architecture-based AI system [8] for facial expression-based emotion recognition is presented. With accuracies of 70.14 and 98.65 percentages accordingly the approach was assessed using the Facial Emotion Recognition Competition (FERC-2013) demonstrating its effectiveness and difficulty as a social communication research topic. The function of personality features in predicting mental health has also been extensively studied in along with emotion detection. In order to categorize people according to their personality traits which include attributes like integrity, extroversion, affability, anxiety and openness personality prediction systems employ a variety of machine learning approaches including logistic regression, support vector regression and neural networks. With applications in fields including mental health evaluations, individualized treatment plans and improving user satisfaction in digital settings these systems frequently employ information from surveys, behavioral patterns or analysis of text to identify personality traits. Rochin et al. investigates how learners' interpersonal health in Industry 4.0 [9] is impacted by the Big 5 Personality Traits. The most important characteristic was agreeableness and Randomizable Filtered Classification techniques demonstrated the highest accuracy. Alexander III. Et al. examines the possible advantages and difficulties of measuring personality using big data [10]. It offers

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a framework for handling big data in character science, an overview of its application in studies of personality a guide to the technology that produce it and a discussion of the value of interdisciplinary cooperation. Stachl et al. perform study and evaluate personality is changing as a result of the increasing availability of high-dimensional information [11] about how people act, such as digital footprints and mobile sensing studies. This data is ideally suited for machine learning algorithms which enable researchers to simulate intricate relationships and assess findings.

3. Data Collection & Preprocessing

This work collects data in a variety of ways including real-time user input for mental health forecasts and databases pertaining to emotions and personality. OpenCV which enables the gathering of emotions from live video feeds is used to acquire visual data in real-time for emotion identification. By using the CNN model to analyze facial expressions this real-time capture allows the system to identify a variety of emotions, including anger, contempt, disgust, fear, happiness, neutrality, sadness and surprise. To ensure that the model can adjust to individual differences in expression, user-specific video feeds are added to the publicly available emotion classification datasets that provide the image info used for learning the model. These datasets include images of faces labeled with the equivalent emotional states. Questionnaires and user input are utilized to gather data for personality prediction. A logistic regression model is trained using responses pertaining to attributes such as dependability, extraversion, seriousness, liveliness and responsibility. Self-reported tests or behavioral questionnaires are commonly used to collect this data which offers insight into a person's psychological makeup. Additionally in order to improve the personalized experience data from the YouTube API [12] is used to provide video recommendations that are specific to the user's personality attributes and anticipated emotional state. The integration of personality tests, real-time mood data and other content sources guarantees that the tool can offer a thorough individualized mental health forecast and support system. For machine learning algorithms [13] to be more robust especially when it comes to emotion recognition data augmentation is crucial (as shown in Fig.1). Data augmentation methods [14] are employed to artificially increase the training data because facial expression databases are frequently small or inadequately varied. This ensures that the model performs well when applied to new unknown data. When employing CNNs for emotion recognition data augmentation techniques including picture rotation, flipping, zooming and moving are used to produce variations of the input images from the original dataset of face expressions. This makes the model more robust to changes in scale, position and lighting that may arise during real-time identification of emotions. During the data preprocessing, Synthetic Minority Over-sampling Technique (SMOTE) is used to solve the class imbalance that might arise in personality prediction and emotion detection tasks. In situations where certain emotion classes, like "Anger" or "Fear" may have less samples than others like "Happy" or "Neutral" SMOTE [15]is very helpful. SMOTE helps equalize the dataset by creating artificial data from the minority categories which keeps the algorithm from being skewed against the majority class. To ensure that the model obtains a more fair representation of each individual's feelings this is accomplished by interpolating among existing samples to create new examples of the minority class.

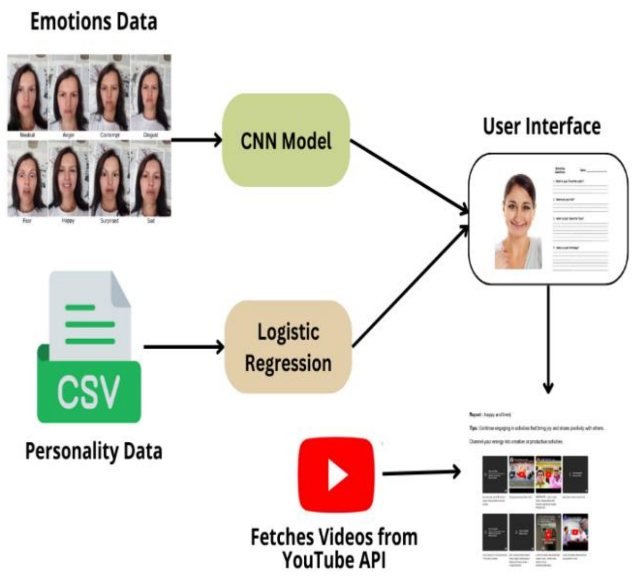

Figure 1Working Methodology

To confirmation that machine learning algorithms can learn effectively and efficiently preprocessing of the gathered data is an essential step. Preprocessing for emotion detection includes a number of crucial procedures including scaling and image normalization. In order to maintain consistency throughout the collection the raw facial photos are scaled to a standard size. To assist the algorithms converge more quickly during training normalization is then done to the pixel values usually scaling them to an amount between 0 and 1. Encoding categorical variables like "extraverted" or "serious," into mathematical representations that machine learning models can comprehend is part of the data preprocessing process for personality prediction. In order to set up it for analysis any text-based personality characteristic data that may be available is also tokenized and stop words eliminated. Additionally, feature scaling is carried out particularly for quantitative inputs where methods such as standardization or min-max scaling [16] are used to guarantee that each feature makes an equal contribution to the model's training phase. Additionally, depending on how severe the missing values are any incomplete or missing data points are either removed or filled. The data input into the models for machine learning is offered to be clean, consistent and prepared for exact predictions thanks to these methods for preprocessing. Figure 1 shows Working Methodology.

4. Convolutional Neural Networks

Convolutional neural network (CNN) is a model for deep learning [17] that works very well for tasks like image identification and classification. It is mainly designed for analyzing structured grid-like input like images. CNNs are made up of multiple layers that use raw input data to learn increasing complex features (as shown in Fig.2). Convolutional sections, layers for pooling and fully linked layers are the primary elements of a CNN. CNN is used in this work for recognizing emotions specifically for real-time facial expression recognition. After feeding the network with raw picture data through an input layer the architecture usually consists of a few convolutional layers that identify architectural characteristics like edges, textures and more intricate structures. Following reduction of dimensionality using pooling layers these obtained characteristics are further subjected to fully connected layers for emotion classification. The CNN architecture employed here is made to accurately transform small-scale facial features into emotion labels. Capturing low-level features like edges, corners and patterns in the input image is the goal of the CNN architecture's first convolutional operation. Multiple filters (also called kernels) are applied by convolutional layers which stride over the input image and multiply each region of the image element-wise before performing an addition operation. By learning to acknowledge fundamental structures in the image these filters function as detecting features. The first layers of convolution in an emotion detection system focus on identifying facial features and edges which are crucial for recognizing facial expressions [18]. Despite being simple these characteristics serve as the basis for complex analyses in later levels. Figure 2 shows CNN Architecture.

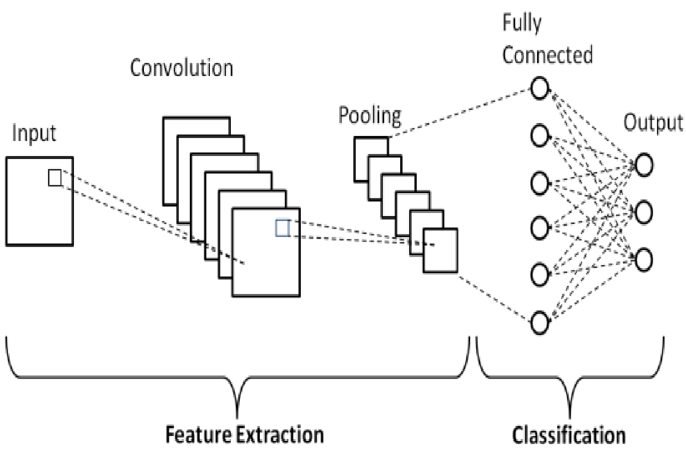

Figure 2 CNN Architecture

A feature map representing the existence of those particular features identified by the filters which are then subjected to an activation function such as ReLU to add non-linearity is the result of the convolution process. By learning to recognize complex patterns like face characteristics (eyes, nose, and mouth) and complex spatial relationships the second multilayer operation expands on the features that were recovered

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by the first array of filters. The convolutional filters in the CNN's deeper layers grow increasingly specialized catching higher-level data like particular emotional expressions. As the network's layers advance from basic edges to complex face patterns that indicate distinct emotions like "Happy" or "Sad" this hierarchical approach learning allows the neural network to concentrate on more abstract data. Through feature map augmentation to highlight important characteristics like the form of the eyebrows or the curve of the mouth these convolutional layers play a crucial role in enabling the model in identifying between identical facial expressions. In order to create a complete representation of the image the final convolutional process usually combines a number of high-level layers that combine all of the previously identified features. The neural network learns to identify patterns that correspond to emotional expressions. The neural network's depth in convolutional layer have significant effects on how well it performs. More complex layers can improve accuracy in the emotion detection process by improving the CNN in detecting small changes in facial movements. Pooling operations like max pooling are used after the last convolutional layers to minimize the physical measurements of the feature maps without eliminating key characteristics. After flattened the inputs is sent to fully connected layers for classification which assigns the learnt features to relevant emotional classes. This CNN architecture with its complex layers and convolution processes provides an effective way to identify and classify emotion-based expressions.

5. Logistic Regression

A popular statistical approach for classification tasks is logistic regression [19] especially where predicting the probability of a single result is the aim. It is frequently used to predict categorical dependent variables with a probability value ranging from 0 to 1 as the result (as shown in Fig.3). In this study personality qualities such as dependability, extraversion and seriousness are determined by input data and logistic regression. Because logistic regression has been developed for binary and several classes problems with classification as opposed to classical linear regression that is utilized for continuous output it is the best option for personality predictions including categories or classes. The logistic regression approach simplifies an outcome between 0 and 1 by employing a sigmoid function to transfer the input data to a probability. This makes it simpler to classify the information into one of the character attribute groups by ensuring that the predictions may be regarded as probabilities. In the framework of personality prediction an algorithm processes input features such as behavioral data or answers to personality-related questions to estimate the probability that a person will display traits like "extraverted" or "lively." Individuals' personality traits are predicted using these probabilities and the output is categorized into several personality types using criteria. Figure 3 shows Work Flow of Logistic Regression.

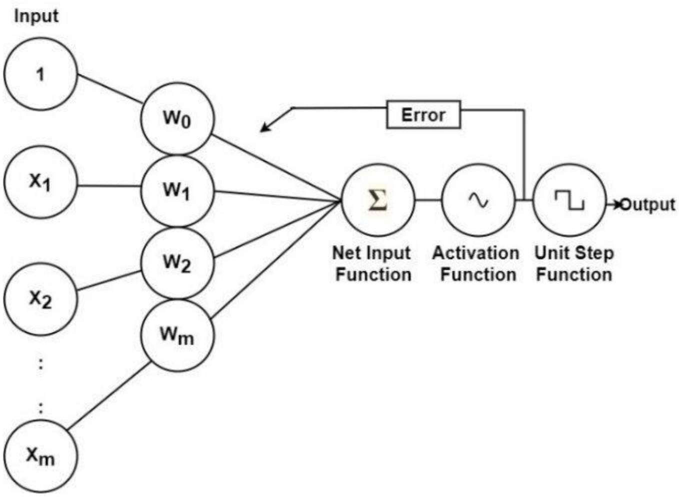

Figure 3 Work Flow of Logistic Regression

According to more complex structures like neural networks logistic regression is easy to comprehend and may reveal relationships between the personality traits and the input characteristics. The parameters of the model illustrate how each trait influences an individual's likelihood of belonging to a specific class. For example characteristics like the frequency of interacting with others or work habits might have a direct impact on a person's likelihood of being labeled as "extroverted" or "responsible" when it comes to personality trait prediction. As a result logistic regression provides practitioners with useful

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interpretability in addition to being a predictive tool enabling them to comprehend the role that particular factors play in personality projections [20]. Logistic regression has drawbacks despite its benefits, the performance may occasionally be constrained by the assumption of a simple correlation between the characteristics of the input and the log-odds of the result especially when the true relationship is more complicated. However, when the connection between the input features and the expected results is roughly linear as is frequently the case in personality prediction exercises when attributes are influenced by quantifiable and consistent behavioral patterns logistic regression performs well. In practice, feature engineering and processing procedures like scaling, normalizing and managing multicollinearity are essential to enhancing the model's performance. Figure 7 shows Navigation Mental Health.

6. Results

Utilizing personality data and facial expressions the works outcomes show how well the models that were put into place were able to predict personality traits and emotional states. The CNN model demonstrated its capacity to accurately classify emotions including anger, contempt, disgust, fear, happiness, neutrality, sadness and surprise with an astounding 94% training accuracy and 100% test accuracy. This excellent performance shows that the CNN can generalize effectively to unknown data and learn strong features from face expressions. The logistic regression approach was employed to predict personality, and it had a 75% accuracy rate on the test set. This is a fair outcome for a personality projection assignment but it also shows that personality qualities are harder to anticipate since they are more subjective and nuanced than emotions which are typically more obvious and instantaneous. Figure 5 shows Confusion Matrix of CNN. Although the logistic regression model's performance for character prediction could be further enhanced with more data or advanced methodologies both models show a high degree of predictive power. The effectiveness of the personality prediction logistic regression algorithm and the emotion detection CNN model was assessed by comparing their respective findings. Figure 6 shows Confusion Matrix of Logistic Regression. Both models' accuracy plots demonstrated major performance differences with the CNN model showing a high test accuracy and a fast increase in accuracy after training. Figure 4 shows Accuracy and Loss Plots of CNN Model.

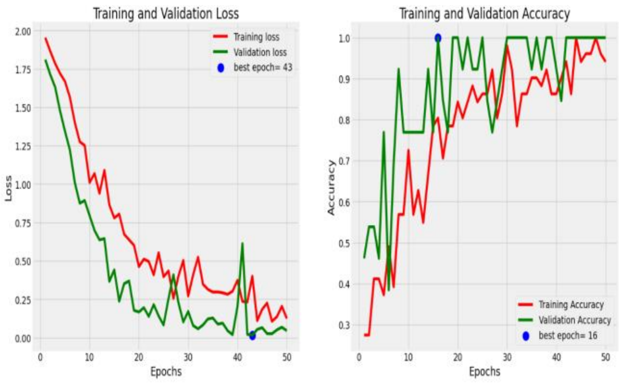

Figure 4 Accuracy and Loss Plots of CNN Model

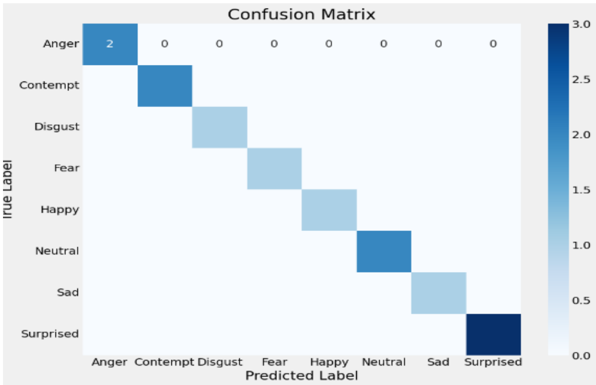

Figure 5 Confusion Matrix of CNN

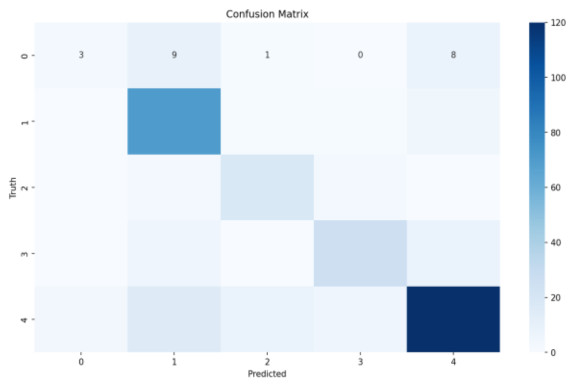

Figure 6 Confusion Matrix of Logistic Regression

Predicting personality traits is difficult as evidenced by the logistic regression model's more slow development and steady but lower accuracy trend.

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Both models' loss plots demonstrated the usual behavior anticipated during training the CNN model showed a quick drop in loss during training whilst the logistic regression framework showed a longer but more consistent drop in loss. These plots show that although both models are useful the CNN model is better at identifying emotions by capturing the spatial aspects of facial expressions whereas logistic regression is good at predicting personality but could use more sophisticated variables or sophisticated methods. Figure 9 shows Real Time Personality and Emotion Based Predictions. With the CNN algorithm achieving almost perfect reliability on the test data the emotion recognition results were quite impressive. The model's capacity to recognize complex patterns in facial images where minute changes in facial expressions signify many emotions is responsible for this classification tasks. The model's usefulness was demonstrated by the effective real-time emotion recognition using OpenCV which recorded users' feelings as they interacted with the system. The system successfully identified emotions including "Happy" "Sad" and "Fear" throughout testing even in dynamic settings with fluctuating illumination and background noise. With few false positives and false negatives the model's performance was reliable. Based on responses to personality-related inquiries or behavioral patterns the logistic regression approach predicted the user's personality by revealing psychological characteristics like extraversion, seriousness or responsibility. Figure 8 shows Web Based User Interface.

Figure 7 Navigation Mental Health

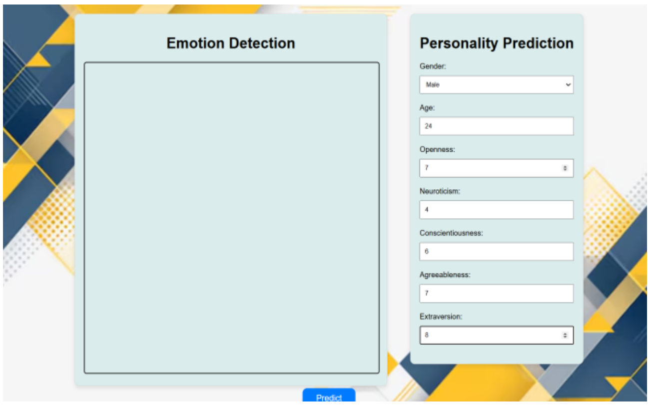

Figure 8 Web Based User Interface

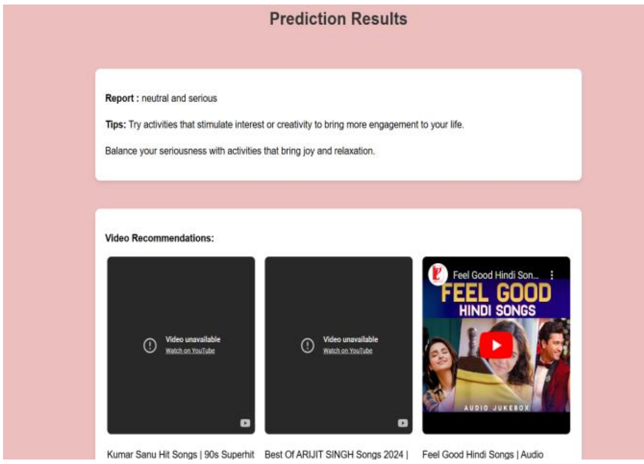

Figure 9 Real Time Personality and Emotion Based Predictions

Although personality prediction is difficult since it is subjective the model's 75% accuracy shows that it still provides useful information about a person's character. Although it occasionally had trouble with people answers were irregular or less representative of the expected attributes the model was often able to accurately identify the key characteristics of users. This demonstrates that in order to manage the heterogeneity in human personality prediction models require more complex feature extraction techniques and a wider variety of datasets. An essential component of the project is the user interface (UI) for Flask-based real-time detection (as shown in Fig.6 & 7) which enables smooth user-system interaction. The Flask-built user interface (UI) offers a straightforward yet user-friendly interface that enables real-time interaction between users and the personality prediction and emotion detection engine. The technology uses a webcam to record the user's facial expressions, processes the data in real time and shows the emotion it detects on the screen right away. The user interface gives consumers an instant grasp of their state of mind by displaying the emotion in real time along with the related personality forecasts. In order to help users enhance their mental health the interface also has a section for suggested videos that are based on the user's expected emotional and personality profile.

Conclusion

By combining machine learning models for personality assessment and emotion detection this work offers a innovative method for predicting mental health. With an accuracy rating of 100%, the CNN model showed remarkable results for real-time emotion identification demonstrating its capacity to correctly identify facial expressions linked to a range of emotions. With a 75% test accuracy the logistic regression algorithm on the other hand successfully predicted personality characteristics and provided insightful information about distinct patterns. The Flask developed real-time user interface (UI) offers an effortless user experience by allowing personality and emotion evaluations as well as customized video recommendations for improving mental health. All things considered the system presents a possible structure for mental health surveillance giving users specific support and quick emotional feedback. However it also draws attention to the difficulties in predicting personality and the need for more development in this field.

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