

Exploring the Relationship between Social Media Behaviour and Mental Health Status

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Abstract - In the internet era, social media plays a central role in shaping human emotions and mental well-being. This research aims to examine emotional expression and psychological states through social media activity by integrating behavioural tracking, facial expression analysis, and deep learning algorithms. The proposed framework introduces a novel method to quantify user engagement by monitoring scrolling patterns, interaction metrics (likes, comments, shares), and real-time facial expressions while viewing multimedia content. A deep learning-based Natural Language Processing (NLP) model is utilized to detect the emotional tone of textual content, while Computer Vision techniques analyze user feedback via facial expression recognition. Additionally, the system tracks user activity over time to identify emotional trends. By integrating these multi-modal insights, the study offers an assessment of users' mental states and proposes interventions such as interactive virtual pets to promote emotional well-being. The research explores two deployment approaches: a custom application that monitors engagement locally and an API-based method that integrates directly with social media platforms. It also evaluates the feasibility, ethical implications, and limitations of each approach. This work contributes to the growing field of AI-based mental health analysis and presents a novel strategy for emotional insight through social media behaviour.

Keywords - AI-based mental health monitoring, deep learning for emotion analysis, facial expression recognition, natural language processing (NLP), sentiment analysis in social media, social media behaviour analysis, user engagement tracking

I. INTRODUCTION

In the last few years, there has been an increase in studies on expressions and mental well-being of people via social media interactions. The subsequent literature reviews attempt to examine what has been researched so far concerning facial expression recognition, social media usage analysis, and their applications in mental health assessment. Existing study methodologies and gaps this present study will address are also researched.

Facial Expression Recognition (FER) has been well studied in affective computing and computer vision. Models based on deep learning such as Vision Transformers (ViTs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) have been found to be highly effective at detecting emotions from facial images. CNN-based Techniques: AlexNet [1, p. 1], VGG [2], and ResNet [3] are highly used for FER. Goodfellow et al. (2013) introduced Deep Belief Networks to classify facial emotions in their

paper [4]. Vision Transformer-based Techniques: ViTs have shown better performance in facial expression recognition because they are capable of modelling long-term dependencies in images [5]. Faster R-CNN in Object Detection: Detection of facial regions has been employed using Faster R-CNN models before emotion classification to boost accuracy in real-time use [6]. Despite these advancements, issues remain in real-world scenarios where changes in lighting, occlusion, and face pose affect recognition accuracy.

Concurrent Natural Language Processing (NLP) techniques have been applied to sentiment analysis of social media text-based emotions. Lexicon-based Approaches: Sentiment lexicons such as SentiWordNet [7] and VADER [8] are applied to determine the emotional tone of text. Machine Learning Models: Support Vector Machine, Decision Trees, and Naïve Bayes classifiers have been employed for sentiment classification. Deep Learning Models: Transformer-based models like BERT [9], GPT [10], and LSTMs [11] have demonstrated enormous leaps in emotion classification accuracy. While NLP methods offer efficient sentiment classification, sarcasm detection, slang, and unclear text detection are difficult.

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Detection of user engagement based on scrolling behaviour has been debated in digital marketing and UX studies. Fast Scrolling Patterns: Imply disinterest or passive browsing (Attfield et al., 2011). Slow Scrolling and Screen Freezing: Indicative of higher levels of engagement and interest (Lalmas et al., 2013). Eye-tracking and Attention Mapping: Eye-tracking devices have been used in some studies to observe reading behaviour and the level of attention. Even though scrolling behaviour provides clues about user interest, coupling this with facial expression analysis remains an unexplored research area.

Evidence has been shown to use online activities for the measurement of mental health disorders, including depression, anxiety, and stress. User Post Patterns: Research conducted by De Choudhury et al. (2013) revealed that linguistic cues from social media posts were capable of predicting depressive symptoms. Engagement Metrics: Negative engagement levels (like, shares, comments) have been connected with deteriorating mental health statuses. Multimodal Analysis: Integrating text, images, and behaviour patterns has been efficient in tracking mental health. Despite these remarks, most studies focus on post-analysis rather than live user interaction.

This research aims to bridge the following existing literature gaps: Combining scrolling behaviour with facial expression recognition to determine emotional responses to social media posts. Utilizing real-time post sentiment analysis of content consumed by users rather than relying on their posted content. Developing a personalized mental health assessment framework from multimodal data. Examining the application of real-time intervention strategies, such as an online pet game, to improve mental health.

II. LITERATURE REVIEW

Social media significantly affects people's day-to-day life, their emotions, their behaviours, and their mental health. Several researchers have explored different ways of analysing human emotions from internet interactions. This research is an extension of current studies in the fields of sentiment analysis, facial expression analysis, and behaviour monitoring to assess users' mental health based on their social media activity.

Researchers have developed various ways to analyse the emotions expressed in social media posts. Sentiment analysis, which is based on Natural Language Processing (NLP), helps determine if a post contains a positive, negative, or neutral sentiment. Deep learning models such as BERT and LSTMs have been widely applied to analyse text-based emotions. Apart from text, multimedia content such as images and videos also play an important role in expressing emotions. It has been found through research that CNN-based models such as ResNet and EfficientNet can successfully identify emotions in pictures.

Facial expressions reflect the emotions of human beings. Several deep learning algorithms, such as Convolutional Neural Networks (CNNs) and Vision Transformers, have been pre-trained with large datasets like FER-2013 [12] and AffectNet [13] to recognize expressions like happiness, sadness, anger, and surprise. These models have already been successfully used to recognize emotions in real-time video streams. Despite this, challenges of light conditions, occlusions, and variability of facial expressions remain.

Particularly with the growth of social media, the application of Natural Language Processing (NLP) for sentiment analysis and emotional identification has become rather popular in the field of mental health research. Previous studies have looked at how social media use affects mental health and shown its influence on emotional well-being. According to Hunt and Eisenberg [14], mental health problems among college students are somewhat common; social media channels provide a possible means of support. According to Moreno et al. [15] sites like Facebook help people to reveal unpleasant emotions, including indicators of

sadness. Additional research by Kross et al. [16] found that regular social media use depresses users' emotional states, therefore lowering their life satisfaction and so strengthening the link between online activity and mental health.

Building on this framework, the current study focuses on using natural language processing (NLP) techniques to identify emotions in social media comments. This is important because it allows researchers to monitor trends in users' mental health. Numerous research has extensively investigated the use of sentiment analysis to extract emotions from text [17] [18]. Meaningful patterns can be extracted from unstructured data thanks to the strong processing capabilities of NLP-based solutions. Tokenization, stop word elimination, and lemmatization, for example, aid in text input refinement, guaranteeing that only pertinent emotional signs are examined. Emotions like joy, sadness, anger, and fear may be effectively identified from text using models like Support Vector Machines and Logistic Regression [19]. The sentiment analysis approaches used in this study are consistent with Marino et al. (2018), who highlighted the necessity for advanced methods to distinguish between various emotions.

Furthermore, according to recent research, NLP may be able to forecast mental health state by classifying emotions in social media content. A potent technique for expressing the level and distribution of emotions in social media content is emotion detection combined with data visualization (such as bar charts). This is especially critical for real-time mental health monitoring and early intervention. The findings discussed here highlight the increasing significance of natural language processing (NLP) in mental health research and offer a strong basis for further investigation into sentiment analysis as a means of gaining insight into mental health through social media behavioural patterns.

Human social media activity, like scrolling speed, post dwell time, and interaction (likes, comments, shares), is informative in identifying the emotional state of a user. Studies reveal that rapid scrolling tends to be an indicator of disinterest, but slowing down at a post or engaging with material is a sign of higher interest. Previous studies have examined how user engagement metrics can be utilized to make an informed hypothesis about emotional reactions, but their integration with facial expression analysis is an unexplored area [20].

There is more and more research being done on how people use social media. Researchers are examining everything from usage patterns and engagement metrics to the psychological effects of online time. Numerous studies are targeting websites like Twitter to ascertain how social media affects our productivity, mental health, and everyday conduct. For example, most researchers log the time that users log on and log off so that they have a clear picture of what they do online. In a study, Jones et al [21]. looked at how long people spent on Facebook, with the suggestion being that longer use was suggestive of potentially addictive usage. In the same vein, Smith and Lee [22] analysed data from mobile apps to detect patterns of over usage and ascertain how these may be correlated with mental illness.

Several studies have tracked closely our use of social media by tracking when we come on and off. For example, Jones and authors tracked how much time users spent on Facebook to estimate their engagement level and whether longer sessions would be predictive of addictive behaviour. In

a similar work, Smith and Lee [22] used mobile app usage data to expose overuse trends and explore the extent to which these trends are related to individuals' emotional welfare.

Furthermore, researchers have still been implementing this on Twitter based on other indicators like the frequency with which they tweet or retweet and during what time of day they are online. Brown and others [23] found that such activity markers, in combination with demographic information and sentiment, can be strongly revealing of social media activity among users. Login and logout times as they happen are a reliable measure of social media usage.

Based on this earlier research, the current paper focuses specifically on Twitter users. Through consideration of the log-in and log-out timing and monitoring the duration of sessions, the current research aims to achieve more profound understanding of social media usage patterns and their resulting behavioural impacts.

Virtual pet games gained more interest during the last three years as an intervention of psychological nature, especially its ability to reduce stress and improve emotional well-being. Virtual pets are software companions that replicate the interaction that living pets will have with others, and with them, creating a sense of emotional support, companionship, and responsibility for the users, Gee and Mueller explains [24]. Studies indicate that virtual pet interaction can support people in their emotional management, stress relief, and enhancement of mental health, particularly for those who are lonely, anxious, or depressed [24].

Virtual pet games are not just fun, they can also improve your mood. They are stressful-less and emotionally comforting. In fact, studies show that virtual pet games can enhance your mood and even lower stress hormones such as cortisol, which is especially helpful for people with depression or anxiety. Through the engagement of interactive play that instills feelings of being part of a community and finding meaning, they are therapeutic antidotes to sad moods that comfort individuals experiencing feelings of solitude or helplessness [25].

Different virtual pets have different emotional advantages. For instance, virtual cats operate to create a calm, laid-back atmosphere, while virtual dogs not only provide companionship but also a calming way of worrying less [24]. On the other hand, virtual parrots can bring light-hearted fun and even have you talking away [27]. Positivity and well-being for the mind are enhanced and interaction by the users are increased due to gamification mechanisms like rewards systems and adaptability based on AI. Virtual pet games now combine artificial intelligence and behaviour analysis to bring virtual pet games into mental health therapy. These smart systems encourage you to open up and take care of yourself more, even helping with cognitive behavioural therapy (CBT) techniques [28] [30]. In short, virtual pet games are becoming a viable, accessible way of fostering mental well-being online [31].

III. METHODOLOGY

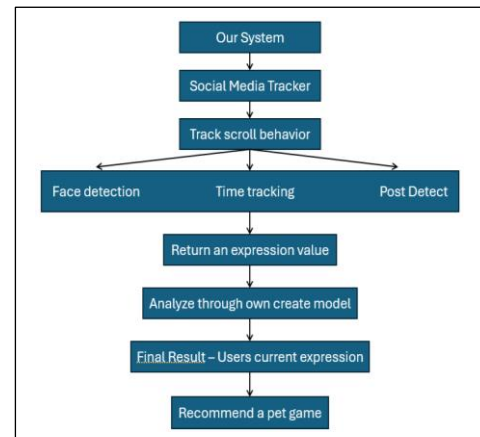


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This research takes a multimodal approach combining behavioural tracking, facial expression analysis, and deep learning techniques to examine systematically human emotions and mental health as expressed in social media use. By combining these different approaches, the research can gather a wide range of data points, from online behavioural patterns of users posting frequency, interactional styles, levels of engagement to indirect non-verbal facial expression cues that may betray internal emotions. The deep learning algorithms, which are learned from large datasets, also enrich the analysis by uncovering intricate patterns and correlations that may elude traditional methods. Such an integrative methodology not only improves our understanding of the emotional dynamics of humans but also provides practical insights into overall trends in mental health that have the potential to underline early identification and intervention in the internet age.

A. Data Collection and Tracking of User Interaction

The system continuously tracks the scrolling activity of the user in real-time to measure the interest of the user in the content. Based on watching the velocity and type of the scroll, the system makes an inference about the level of interest of the user: a rapid scroll is presumed to be a sign of no interest, whereas a slow scroll with halt shows likely interest. If the user scrolling comes to a halt for five seconds or longer an extended screen freeze this can be taken as an overt indicator of high interest. Along the way, the system captures the post currently being displayed as well as how long it lingers on-screen, providing useful data for use in future research on user attention.

Once the user pauses scrolling for a noticeable duration, the system activates the device camera to capture an image of their facial expression. The image is then read using a convolutional neural network (CNN) that determines the expression as belonging to one of seven predetermined emotion classes—happy, sad, angry, fear, disgust, surprise, or neutral. Facial expression data is also synchronized with the content currently viewed at that exact moment and, in a sense, aligns the user's mood with the actual post on the screen.

Furthermore, according to recent research, NLP may be able to forecast mental health state by classifying emotions in social media content. A potent technique for expressing the level and distribution of emotions in social media content is emotion detection combined with data visualization (such as

bar charts). This is especially critical for real-time mental health monitoring and early intervention. The findings discussed here highlight the increasing significance of natural language processing (NLP) in mental health research and offer a strong basis for further investigation into sentiment analysis as a means of gaining insight into mental health through social media behavioural patterns.

```
test_generator = datagen.flow_from_directory(
    # 'path_to_dataset', # Replace with the path to your dataset
    new_test_dir,
    target_size=(48, 48),
    color_mode='grayscale',
    batch_size=batch_size,
    class_mode='sparse',
    subset='validation')

loss, accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {accuracy * 100:.2f}%")

Found 883 images belonging to 7 classes.
28/28 ————— 2s 56ms/step - accuracy: 0.3756 - loss: 1.54
Test Accuracy: 36.69%
```

fig

```
predictions = model.predict(img_array)
emotion_labels = ['Angry', 'Happy', 'Sad', 'Disgust', 'Fear', 'Neutral', 'Surprise']
predicted_emotion = emotion_labels[np.argmax(predictions)]

print(f"Predicted Emotion: {predicted_emotion}")

1/1 ————— 0s 189ms/step
Predicted Emotion: Sad
```

fig

B. Processing of Data and Analysis

Processed text and image content is examined through a two-model classification system that expresses its emotional tone in a very humanized form. In the case of the text portion, a Natural Language Processing (NLP) model explores the subtleties of language considering context, nuances of language, and the overall message before classifying the sentiment as positive, negative, or neutral. Similarly, in the event of image-enabled posts, there is a CNN-based classifier which is typically formed on the back of architectures like ResNet and carefully scans for visual signals. It takes colour, facial emotion, and overall image composition into account to crack the emotion embedded. By combining the information from the NLP model with that from image processing, the system can deliver a holistic and human-perceived understanding of the post's sentiment, including the analytical facts as well as the rich, subtle emotional narrative.

At this level, the system equates the recorded facial reactions of the user to the emotional context of the post being viewed. Essentially, it maps each recorded facial reaction such as a smile, frown, or otherwise back to the specific content type of the post. This mapping enables the system to record and analyze per-content category user response patterns. This way, one can determine the type of post and the nature of the emotional response generated by them and thus can measure the user engagement and how content impacts the emotional state of the user.

Here, the time a user spends on different posts is carefully monitored and linked with various behavioural metrics to gauge emotional influence and predict shifting behaviour patterns. By linking scroll speed, facial expression data, and social media metrics such as likes, comments, and shares, the system creates a comprehensive profile of user interactions. The speed of scrolling can indicate lesser interest as a quicker scroll, whereas slower scrolling with the inclusion of positive or negative facial expressions indicates greater emotional engagement. The engagement metrics also provide insight by quantifying active user engagement with the content. These data points combined enable having a clear vision of the emotional reaction users have towards content and being able to forecast subsequent behaviour patterns.

C. Data Fusion and Mental Health Assessment

The system combines diverse data sources in a synergistic manner to form a grand view of user interaction and emotional response. It combines scroll behaviour data, which indicates the user's level of interest in terms of navigation within content, with post emotion categorizations that demonstrate the emotions exhibited in response to different posts. Moreover, user engagement metrics i.e., likes, shares, and comments are collected alongside facial expression analyses, that capture real-time emotional signals through the use of deep learning algorithms. Through a combination of these variables, the system generates an organized dataset that captures and aligns user emotional responses to various types of content, thereby enabling a richer understanding of the emotional attraction of various types of content.

The system uses a time-series analysis to monitor a user's emotional state over an extended period of time, identifying any persistent negative trends. It then follows repeated instances of sad, angry, or disengaged facial expressions, which can serve as early warning signs of emotional distress. In addition, the measurement tracks behavioural indicators such as sustained screen freezes on the negative-tensed posts, which implies that these parts of content are exerting a profound emotional impact. The system also analyses the frequency of interaction with the negative content. By combining these indicators, a pattern analysis algorithm can flag long-term negative emotional patterns, thus providing insightful knowledge that can initiate early intervention or additional evaluation of the user's mental health.

The system monitors the user's emotional responses continuously, and whenever a negative pattern is formed, it provides feedback regarding the likely reasons. For example, it may inform that the user is being exposed to increasingly more negative content, has a lesser response towards positive content, or experiences changes in emotional responses. From these patterns, the system creates a comprehensive report of the user's emotional engagement that can serve as an early warning indicator for mental illness.

The Mental Well-Being Recommendation System is targeted at identifying long-term negative trends in online behaviour and emotional responses of an individual and actively suggesting customized interventions for improving mental well-being. When the system detects consecutive periods of negative signals, it starts a series of recommendations: one is an online pet game, which serves to facilitate interaction and offer a positive interactive experience; another is to prompt the user to view positive

content with the potential to enhance their mood; and finally, the system may recommend social media breaks to be taken in order to reduce stress and facilitate healthier mental balance.

D. Implementation Strategies

Imagine an app employing a specially designed social media browser and WebView monitoring to collect real-time observations of how people engage online. This new approach not only observes how people scroll through their feed and view content on their screens but also captures their facial expressions to observe what they think about it. While this method is full of insights into user interaction and consumption of content, it has severe pitfalls too. For instance, privacy protection for users and appropriateness in securing due consent are critical. Further, the process also gets complicated due to platform constraints, where some social networking sites actively filter WebView tracking, thereby making it difficult to collect data.

Social Media API-Based Monitoring leverages official social media site APIs to collect fine-grained user interaction data, allowing for direct integration with the sites to monitor engagement in the form of likes, shares, and comments. This method has a significant issue, however. The first is that the APIs usually have limitations that restrict access to certain user content, hence affecting the availability of the data. Second, without real-time screen monitoring, capturing fine-grained information such as user scrolling patterns is problematic, and as such some user engagement data are not captured.

E. Processing of Data and Analysis

This assessment method employs a blend of diverse data sources to measure mental health status. It integrates textual sentiment analysis, image-based emotion detection, interaction patterns, and time-sensitive data to form a comprehensive input profile. In this approach, text data from social media posts is analysed to detect sentiment, and facial images are analysed to classify emotions. Concurrently, usage patterns of the user and when they happen are recorded to provide meaning to engagement behaviour. All these multi-modal inputs are then fused and processed by a Support Vector Machine (SVM) model to make predictions regarding the overall emotional state and mental health condition of the user.

The flowchart mimics a sequence of research activity that is triggered by the user's surfing behaviour on social media. The system first tracks the scrolling behaviour of the user to record real-time user engagement metrics. The following is posting emotion classification through natural language and image processing, which analyses the emotional sentiment and visual features of posts. Meanwhile, the system also employs a convolutional neural network (CNN) to recognize and classify the facial expression of the user, mapping their emotional state to whatever is being viewed. The scrolling behaviour data, after emotion classification, and facial expression recognition data are then merged and analysed to estimate overall user engagement. The merging of the data

enables the extraction of emotional trends, which powers mental health assessment. After this detailed analysis, the system ultimately employs a recommendation engine that suggests interventions in a virtual pet game and positive content, for example to support and enhance the user's mental well-being.

Visual interpretations of the data collected provide a tangible and intuitive means to discover more about user behaviour and emotional response when viewing content. One instance of this is when, as you chart scrolling behaviour with measurements for engagement, you can observe how varying scrolling speeds, i.e., fast swipes vs. laborious, questioning pauses, map to actions like likes, shares, or comments. Furthermore, a graph that graphs the spread of facial expressions while reading material offers a snapshot of what feelings are most felt immediately, allowing us to see what feelings dominate as a reaction to various types of material. Lastly, an emotion-tracking time series graph measuring how emotional responses over time can show shifting trends and minor mood shifts as users continue on their streams, helping to identify patterns or stimuli that influence their emotional state.

IV. RESULT AND DISCUSSIONS

A. Social Media Behaviour

Social media has become an integral part of our daily lives, influencing not just the way we communicate but also the way we feel. In this study, we learned how people interact with posts, how they respond to different content, and what their social media behaviour can say about their emotional and mental health. In order to do this, we collected data from sources like Twitter (X), Reddit, and Instagram, with emphasis on:

- 1) *Text (tweets, captions, comments)*
- 2) *Images (memes, profile pictures, posted images)*

B. How Images Affect Emotions Online

Surfing on social media is a visual experience. Pictures, memes, and even profile photos convey emotions more than words can ever do. By using deep learning models, we scanned thousands of pictures and saw some clear patterns:

Funny memes and interesting pictures put people in a good mood and relaxed them. Disturbing or depressing photos (e.g., news of tragedies, personal catastrophes) tended to cause fear, worry, or sadness. Selfies and profile pictures played a fascinating role those with smiling or expressive pictures were more inclined to engage, whereas the ones with neutral or scowling pictures were less likely to engage. Takeaway: Social media photos can impact our mood. Happy and humorous photos boost mood, and sad pictures can generate distress.

C. How People Interact with Social

Aside from what individuals view and read, the way they interact with material is even more revealing about their psychological condition. We tracked user behaviour how quickly they scroll through, where they would stop, and how long they spend on a post and found these patterns:

- Fast scrolling → Individuals skip over

content they are not interested in.

- Slow scrolling + pausing → This signifies the material caught their attention.
- Long screen freeze → Indicates high engagement, possibly an emotional reaction to the post.
- Repeated views → Repeat visitors of the same post are typically emotionally invested in the content.
- Late-night browsing → Users tend to engage with emotional or negative content during late nights, possibly because of stress, overthinking, or even loneliness.
- Takeaway: The way we scroll on social media tells us a lot about our mood. People who scroll through depressing or negative updates regularly may be stressed or have emotional problems.

D. The Broader Context – Ethics, Privacy & Future Possibility

- While such findings are certainly interesting, one must also view them through a lens of ethics and privacy considerations. People must be in control of the application of their information, and artificial intelligence systems need to be made to help manage mental health not invade privacy.
- In the future, this research can potentially point towards AI-grounded mental health technologies, i.e.,
- A social media feature that suggests uplifting content to a user when they have been subjected to excessive negativity.
- A personal AI friend that browses history and offers well-being tips.
- A mental wellbeing monitors that alerts user if their online behaviour suggests emotional distress.
- Last Thought: Social media mirrors our minds. By learning how we engage with it, we can create improved tools for enhancing mental well-being in the digital age.

V. ACKNOWLEDGMENT

Today, our study looks at text, images, scroll patterns, and expressions separately to determine how one feels when they are on social media. Useful information, to be sure, but it is not without its limitations feelings are nuanced and often dependent on multiple variables at once

A better way would be to put all of these data streams into one AI system and have it scan all of them simultaneously in real-time. This way, instead of breaking up emotions into parts, we are able to see a much improved and more precise picture of what a person is feeling.

We recommend using a multimodal deep learning model, i.e., AI for text, image, facial expression, and user

behaviour analysis all together. This is how each part would work:

Better Image & Facial Expression Processing using Vision Transformers (ViT). Instead of the traditional image models (e.g., CNNs), we can use Vision Transformers (ViT), which process small facial cues and emotions much better. This would make our system more accurate in detecting emotions from images or user faces. More Advanced Text Comprehension with Large Language Models (LLMs). Simple sentiment analysis these days tells us if a post is positive or negative. But emotions are not always that black-and-white! With advanced AI models such as BERT or GPT, we can detect sarcasm, mixed emotions, and nuanced meanings in text just like humans do. Smart Tracking of Scrolling Behaviour. Instead of measuring the scrolling speed in isolation, we can measure it in relation to a post's emotions and see how an individual reacts in real time.

If, for example, an individual stays for some time on a melancholic post and their facial expressions show sadness, our system can match these actions against one another. Placing Everything Together into a Smart AI Model. Instead of looking at text, images, and behaviours individually, we'll train an AI model that learns how to balance all these factors. This model will figure out which data is most important in each situation and combine it for a more complete emotional analysis.

How Is This Better Than Our Current Research? Today's system relies on independent analysis for text, images, and behaviour, whereas the future system will integrate all of these in real-time for more sophisticated detection. Image processing uses CNNs at present, which are efficient but are limited compared to Vision Transformers (ViT) that will allow for more accurate facial emotion reading. Text sentiment analysis is today restricted to simple positive or negative views, but future applications will utilize advanced AI models like BERT and GPT to identify nuanced emotional undertones. User behaviour tracking meanwhile focuses on scroll speed only, but the upgraded version will use scrolling information, facial recognition, and text for a more comprehensive understanding. Lastly, today's output has to be manually merged into individual results, while the next system will do all the merging of the channels of information into giving a richer, more consolidated view into users' emotions.

With this cutting-edge AI system, we can:

- Accurately identify emotions by reading multiple sources in parallel.
- Provide real-time feedback rather than commenting on emotions in a vacuum.
- Provide improved mental health guidance based on the entire emotional context.

This release will take our study from simple tracking and build a smarter, AI-based emotion analysis system that truly understands what people are experiencing when they're online.

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