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An Agent-Based Multilingual Social Media Behavioral Analysis using XLM - RoBERTa Multi-Task Learning

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Abstract: Understanding multilingual social media behavior over time is hard because online archives hold large and varied informal posts and because people talk and interact in ways that keep changing. The paper introduces an Agent-Based Framework for Longitudinal Multilingual Social Media Behavior Analysis that uses XLM-RoBERTa based Multi-Task Learning. The framework uses software agents to collect archives pull out data, clean multilingual text analyze behavior organize data over time create profiles and show results. Social media records that include posts, comments, messages, replies and activity data are looked at in 3-, 6- and 12-month windows to find patterns and trends. XLM-RoBERTa is used with heads for sentiment, emotion and hate speech analysis. Experiments show 79.96% accuracy and 77.49% Macro F1 for emotion, 69.15% accuracy and 69.27% Macro F1 for sentiment and 83.07% accuracy and 82.68% Macro F1, for hate speech. The framework gives dashboards for statistics, time trends, engagement, language and interaction. Results show that combining agent-based processing, multilingual transformer learning and longitudinal analysis can give a picture of multilingual social media behavior.
***Keywords:** Agent-Based Framework, Multilingual Social Media Analysis, Multi-Task Learning, XLM-RoBERTa Behavioral Prediction, Longitudinal Behavioral Profiling.*

I. INTRODUCTION

Understanding how people behave on media over time is a big challenge. Social media has a lot of information about how people talk to each other what words they. How they interact with each other. We get this information from posts, comments, messages and replies. When we look at all these interactions together we can understand how people behave and communicate with each other on media. It is tough to get information from media because people use different languages and write in casual ways. Also the way people interact with each other on social media changes over time. This makes it hard to figure out what is going on.

Recently new language models like BERT, RoBERTa and XLM-RoBERTa have become very good at understanding text in languages. XLM-RoBERTa is particularly good at understanding languages at the same time. This is a help.

Most studies use these models to look at social media posts or try to predict one thing, like how someone is feeling. They use models for different tasks, which can be complicated and hard to scale. These approaches do not show how peoples social media behavior changes over time. So we only get an understanding of how people communicate with each other on social media.

To fix these problems this paper proposes a framework for analyzing social media behavior. This framework uses a shared model to predict things, like sentiment, emotion and toxicity all at the same time. It looks at all of a persons media interactions over a period of time like 3, 6 or 12 months. Then it uses this information to create a picture of how someone behaves on media.

The framework can handle media posts in many languages, including English, Hindi and Telugu. It provides insights into social media behavior through an interface and interactive dashboard. By using automation, multilingual models and looking at social media behavior over time the framework provides a solution for analyzing social media behavior, which's social media behavior. The framework is, about understanding social media behavior and it does this by looking at social media behavior in a new way.

II. LITERATURE REVIEW

The availability of social media data in languages has sped up research in Natural Language Processing, language models that use transformers learning that involves many tasks and systems that use intelligent agents. Social media platforms produce a lot of content in languages and mixed codes that show how users communicate and interact online.

It is still hard to really understand how users behave because of the many languages, informal writing styles and how user activities change over time. Some recent studies have looked at understanding languages in languages analyzing behavior over time learning that involves many tasks and intelligence that uses agents. With these advances most approaches look at these areas separately which limits their ability to give a complete picture of user behavior.Models that use transformers to understand languages have made it easier to analyze social media content that is in many languages and mixed codes. Some studies show that using the techniques to prepare and identify languages and to make them standard can improve analysis across different social media platforms. For example using transformer models to analyze sentiment and emotions in media data that is in many languages can improve classification and handle mixed code text well. Although these approaches work well for tasks they do not look at behavior over time and do not give a complete picture of user behavior.

Some recent studies have highlighted the importance of looking at media activity over time instead of just looking at individual posts. Analyzing social media data over time can give an understanding of user behavior and make it more consistent and reliable. However most approaches focus on how users feel and do not look at aspects of behavior such as engagement, conflict and communication patterns. This limits their ability to give a picture of user behavior over time.

Learning that involves tasks has become a popular approach to solve many related tasks at the same time using shared features. Some studies show that using a shared transformer encoder with task- prediction heads can improve efficiency and sharing of knowledge across related tasks. While this approach works well for detecting hate speech it has not been used for analysis of behavior in many languages.The development of Large Language Models has sped up the creation of agent-based systems for social media analysis. Some studies show that using software agents can improve performance through specialization and modular reasoning. Although these frameworks provide intelligent architectures they mainly focus on sentiment analysis and do not integrate language understanding, behavior analysis over time and learning that involves many tasks into a unified framework.

The literature shows that there has been progress in language modeling behavior analysis over time learning that involves many tasks and agent-based intelligence. However there are still challenges. Most approaches analyze social media posts instead of activity over time which limits their ability to capture how behavior changes over time. Many studies focus on tasks and require separate models, which increases complexity and limits sharing of knowledge. Furthermore there is research that integrates language models that use transformers behavior analysis over time learning that involves many tasks and autonomous software agents into a unified framework that can give a complete picture of behavior from social media archives.

To address these limitations this paper proposes a framework that uses agents to analyze social media behavior in languages using learning that involves many tasks and transformers. The framework uses software agents to process social media archives collected over periods of 3, 6 and 12 months. A shared encoder integrated with -task learning predicts many aspects of behavior such, as sentiment, emotion, toxicity and engagement level. These aspects of behavior are analyzed over time to construct a picture of behavior that captures communication patterns, engagement dynamics, language usage and behavior evolution based on online interactions. Natural Language Processing and language models that use transformers are used to analyze media data in many languages. The framework gives a picture of user behavior and can be used to analyze social media archives

III.SYSTEM ARCHITECTURE AND DESIGN

The suggested a framework that uses a setup with agents to look at how people behave on social media over time in different languages. This system is different from looking at each post on its own with models. It brings together software agents, XLM-RoBERTa Multi-Task Learning and time-based thinking into one system.The way it is set up allows the agents to work on their own and talk to each other in a way. They can handle a lot of media data that is in different languages. The whole setup is shown in Figure 1.

This system has an Agent Coordinator and different types of agents. The Agent Coordinator manages the work by setting tasks helping the agents talk to each other and watching what is happening. Each agent does its job. Shares the same kind of information. This makes the social media system easy to change grow and add parts to.The Data Acquisition Agent checks the social media data that people upload. This data can be in formats like CSV, JSON, TXT or ZIP. The Archive Processing Agent takes this social media data. It pulls out posts, comments, captions, messages, replies, metadata and times when things were posted. The Data Structuring Agent turns all this social media data into one format.

Then the Multilingual Preprocessing Agent works on it by finding out what language it is making it consistent breaking it into parts and cleaning up any stuff. This part handles social media content in English, Hindi, Telugu and languages that mix words.The Behavior Intelligence Agent is the part of the social media system. It uses a XLM- encoder that is part of a Multi-Task Learning setup to create language-based information.

The same encoder has parts that predict things like how someone feels what emotion they have if something is rude if they are upset how strong their feelings are, if there is a conflict and how much people are engaging. This social media setup helps share parts between jobs, which makes it better at learning about different languages and saves computer time.To fix the problems that come with looking at one post at a time the Temporal Intelligence Agent looks at behavior over time by putting together predictions from time periods. These time periods can be 3, 6 or 12 months. The agent finds out how people behave over time how they communicate and how their actions change. This helps study how people act over a time not one moment.

The Behavioral Profiling Agent takes the social media information from the time periods. It puts it all together into one long-term view of how someone behaves on media. This view shows how people talk what emotions they have, how they act, which languages they use, how they deal with conflicts how they express themselves and how their way of acting changes over time. This view is the way the social media system understands behavior.The Visualization and Analytics Agent shows the view of behavior using dashboards, reports and ideas that help people understand and make decisions about media.This social media system brings together how agents work together how to handle languages with a special kind of learning how to predict behavior in different tasks and how to look at time all in one place. The way the agents work together makes it possible to look at languages and find out about behavior over time from social media data, on social media.

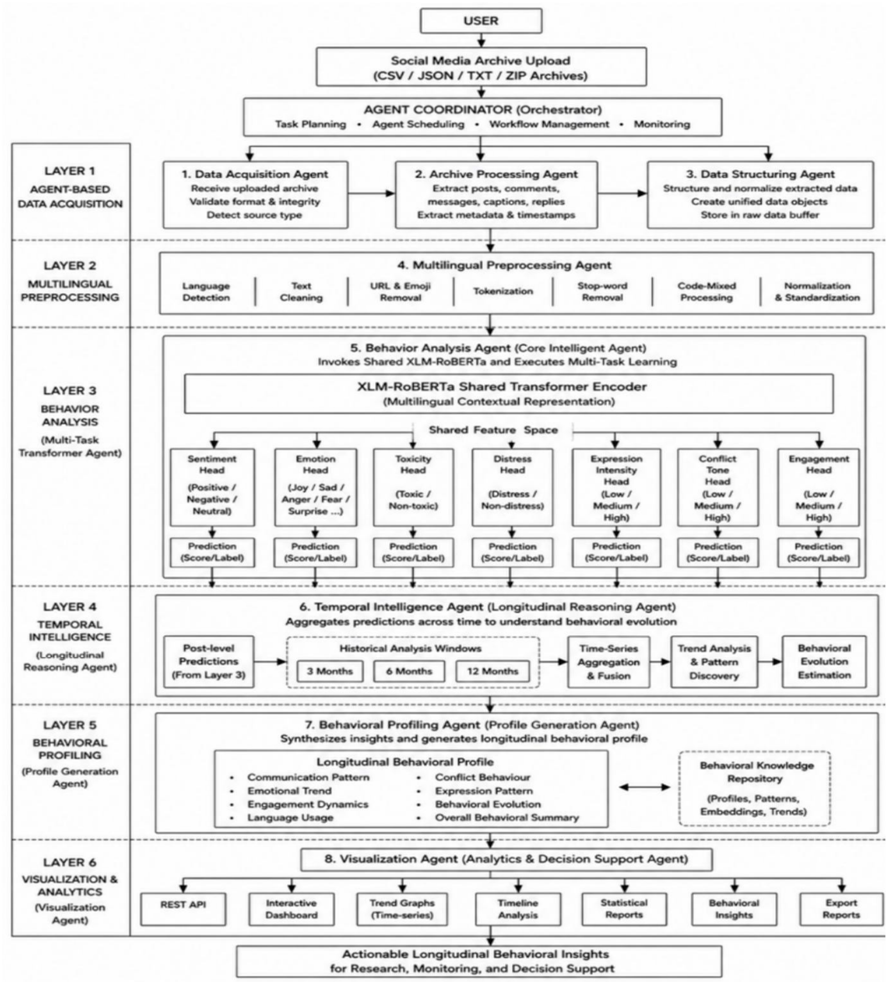

Fig 1 : Overall Proposed Architecture

IV.METHODOLOGY

The approach uses an agent system to do long-term analysis of social media behavior in multiple languages using old social media records. The system uses software agents, multilingual transformer learning, multi-task behavior prediction, and time-based intelligence to create detailed user behavior profiles. The full process has seven steps: getting data, preparing it for use, making features predicting behavior using time-based intelligence making behavior profiles and showing the results. The whole method is shown in Fig. 2.

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A. Data Ingestion and Structural Parsing:

Choosing datasets is very important for making a strong system for multilingual behavior analysis. No one dataset has all the information needed for sentiment, emotion, toxicity and distress expressions in languages. So this study uses different datasets to make a complete multi-task learning collection. The chosen datasets together offer types of language behavior information and social media situations needed to train the XLM-RoBERTa system.

Go Emotions, made by Google Research has around 58,000 Reddit comments with 27 emotion types and a neutral class. It is often used for emotion recognition. For checking for language in many languages the Jigsaw Multilingual Toxic Comment Classification dataset has hundreds of thousands of comments in different languages. This helps the model understand language in different places. To get expressions of stress that people often share online is used. It has 190,000 Reddit posts that are marked for stress-related words. It helps find signs of stress without trying to understand health. Real code-mixed communication is shown with the SentiMix dataset, which has Hindi- posts marked for sentiment. The Dravidian-CodeMix dataset has Telugu- code-mixed comments marked for sentiment and offensive language.

Unlike studies that only use datasets this system also looks at old social media records that people upload. These records have posts, comments, replies, captions, times and other information collected over time. The datasets are used for training the -task model and the old records are used for looking at behavior over time with the multi-agent system.

The datasets used offer a lot of language variety by including ways of writing many languages, code-mixed language user-created content and different ways of showing behavior. This variety helps the system learn general language patterns and do full behavior analysis in English, Hindi, Telugu and mixtures of these languages.

Social media data has messy and not organized parts like links, emojis, hashtags, mentions, HTML, special letters and informal language. This can hurt how multilingual text works and how well transformer models perform. So a process is used to clean and make the data the same while keeping meaning.

At first things that are not needed like HTML, links, special letters and repeating symbols are taken out. Mentions and hashtags are kept if they help with meaning. Informal words, slang, abbreviations and spelling changes are made into forms. For example "gud" becomes "good" and "idk" becomes "I don't know".

After making things normal the text is broken into parts for use with languages. This step makes an same way to show text for using with the XLM-RoBERTa model.

B. Tokenization and Sentence Segmentation:

Tokenization is a step for transformer models because it changes text into small parts that the model can use. In this system the multilingual text is split into parts using the SentencePiece tool that comes with XLM-RoBERTa. SentencePiece splits words in a way that works for any language making it easier to handle languages and mixtures of languages and reducing problems with words that are not known.

For media data splitting into sentences is done to keep the meaning of posts, comments and replies before splitting into parts. This is especially important for languages and mixed language text, where wrong splitting can change the meaning and hurt behavior prediction. The parts are then turned into meaning-based pictures by the XLM- tool for more work on behavior.

C. Handling emojis and informal text:

Social media text often has emojis, short forms, slang and informal phrases that show emotion and context. Of removing these the cleaning process changes the emojis into their real meaning (like into happy) to keep the meaning. Also common short forms and informal phrases are made into words (like "idk" into "I don't know" and "gud" into "good"). This makes the language more the same while keeping the meaning making it better for the XLM- model to work with.

D. Language Identification and Code-Mixed Text Handling:

Correctly finding the language is important for looking at many languages especially for text that mixes languages. The system finds the language of each social media item and works with English, Hindi, Telugu and mixtures of these languages.

After finding the language the cleaned text is directly used by the XLM- multilingual tool, which learns a shared meaning across many languages without needing models for each language. This helps the system keep the meaning and context in languages and mixed language text making the behavior prediction better.

E. Multilingual Feature Representation:

1) XLM- RoBERTa Embedding:

After cleaning the multilingual social media text is changed into meaning-based pictures using the XLM-RoBERTa model. XLM-RoBERTa is a model for languages that is trained on a lot of text, which helps it learn the same meaning across different languages. This makes it good for looking at languages and mixed language text, including English, Hindi, Telugu and mixtures of these.

Let, $$x_i'=(t_1,t_2, t_3, \ldots..t_n\ ) \quad (1)$$

Denote the prepocessed token sequence of the i^{th} social media record where n sequence length.

$$h_i=\text{XLMR}(x_i') \quad (2)$$

Where $x_i'\in X$ is the cleaned parts, XLMR(·) is the XLM- tool $h_i\epsilon$ ℝd is the meaning-based picture ,d is the size of the picture.

2) Shared Feature Projection:

To get a way to use for tasks the meaning-based picture is changed into a common space using a simple step

$$z_i= W_s h_i\ + b_s \quad (3)$$

Where , $W_s\in\mathbb{R}^{m\times d}$ is the step that changes the picture ,

$b_s \in\mathbb{R}^{m}$ is the step that adds a value ,

$z_i\in\mathbb{R}^{m}$ is the common picture m is the size of the common space.

Since $W_s\in\mathbb{R}^{m\times d}$, $h_i \in\mathbb{R}^{d}$,$b_s\in\mathbb{R}^{m}$ the changed picture is $z_i\in\mathbb{R}^{m}$ The common picture $z_i$is used as input for tasks like sentiment, emotion, toxicity, distress expressions, conflict tone, expression intensity and engagement. By learning the meaning in a shared space XLM-RoBERTa helps the system understand the meaning, grammar and different languages in many types of social media.

3) Multi-Task Behavioral Learning:

The common picture from the step is used to predict behavior things at the same time. Of making a model for each behavior the system uses a way called multi-task learning, where a common tool is used with different parts for each task. This helps the model learn the meaning while keeping the different parts for each task making it better and learning less.

Let, $$\text{T} =\{ T_1,T_2,T_3\ldots\ldots T_k\} \quad (4)$$

be the list of behavior tasks, where K=7 in this system:

$$\text{T}=\{T_{\text{sent}}, T_{\text{emo}}\ , T_{\text{tox}}\ ,T_{\text{dist}}\ , T_{\text{conft}}, T_{\text{inten}}\ , T_{\text{engt}},\} \quad (5)$$

Which are Sentiment Analysis, Emotion Recognition,Toxicity Detection, Distress-related Expression Detection,Conflict Tone Classification, Expression Intensity Estimation and Engagement Prediction.Each task gets the picture z_i and uses a different part to make a prediction. For the k_{th} task the chance of each result is

$$\widehat{y_i^{(k)}}=\text{Softmax}(W_k z_i + b_k) \quad (6)$$

Where W_k , b_k are the steps for the k_{th} task part y is the chance of the result for task T_k

The task part loss is $$L_k=\mathscr{L}(\ y_i^{(k)}\ \ ,\ \widehat{y_i^{(k)}}\ ) \quad (7)$$

Where $y_i^{(k)}$ is the right result, $\widehat{y_i^{(k)}}$ is the guess , $\mathscr{L}(.)$ is the loss step (like cross-entropy for some tasks).The total task loss is found by adding up all the task losses:

$$L_{MTL} = \sum_{k=1}^{k} \lambda_k L_k \quad (8)$$

Where K's the number of tasks , $\lambda_k\geq 0$ is the step that changes how much each task helps L_{MTL} is the total for all tasks.

The model is improved by making the total loss as small, as possible

$$\theta^*=\arg\min L_{MTL} \quad (9)$$

where theta represents all parameters of the shared encoder, projection layer and task-specific prediction heads. The proposed multi-task learning framework allows knowledge sharing across behavioral analysis tasks while keeping specialized decision boundaries through separate output layers. This joint optimization method improves representation learning for multilingual and code-mixed social media data. Offers a unified behavioral understanding that serves as the base for the next temporal intelligence module.

F. Temporal Intelligence

Behavioral characteristics shown on social media change over time of staying the same. So the proposed framework has a Temporal Intelligence module to analyze term behavioral patterns by combining behavioral predictions across multiple historical time periods. This helps spot trends while cutting down the effect of short-term changes.

Let, $$P = \{(\hat{y}_1 , t_1)\ (\hat{y}_2, t_2) \ldots\ldots (\hat{y}_N, t_N)\} \quad (10)$$

be the order of predictions,

Where $$\hat{y}_i = [\hat{y}_i^{(1)} ,\ \hat{y}_i^{(2)},\ \hat{y}_i^{(3)} \ldots\ldots \hat{y}_i^{(k)}] \quad (11)$$

is the behavioral prediction vector created by the Multi-Task Learning module for the i^{th} media record t_i is the related time stamp N is the total number of past social media records K is the total number of behavioral prediction tasks.

The past records are split into fixed time periods:

$$W = \{W_{3m} ,\ W_{6m} ,\ W_{12m}\} \quad (12)$$

Where W_{3m} means the three months W_{6m} means the last six months W_{12m} means the last twelve months.

For each behavioral task T_k, the total behavioral score over a time period W_T is found using weighted averaging:

$$B_T^{(k)} = \frac{\sum_{i \varepsilon W_T} w_i\, \hat{y}_i^{(k)}}{\sum_{i \varepsilon W_T} Wt} \quad (13)$$

Where $B_T^{(k)}$ is the behavioral score of task Tk during time period W_T, $\hat{y}_i^{(k)}$ is the forecast of the kth behavioral task for the i^{th} social media record

$w_i \geq 0$ is the time weight given to the i^{th} record W_T refers to the group of records in the chosen time period.In this work all records in each analysis window get the time weight, which is w_i=1 ∀i $\in W_T$, The weighted method is kept to allow future changes that might add time-decay weighting.

G. Behavioral Profiling

The behavioral trend between two time periods is calculated as

$$\Delta B^{(k)} = B_{T2}^{(k)} - B_{T1}^{(k)} \quad (14)$$

Where $B_{T1}^{(k)}$ and $B_{T2}^{(k)}$ are the scores of task T_k for two time periods, $\Delta B^{(k)}$shows the size and direction of behavioral change.

A positive number means a growing tendency while a negative number means a decreasing tendency over time.Finally the total behavioral profile is shown as

$$B = \{B_{3m}^{(k)} ,\ B_{6m}^{(k)} ,\ B_{12m}^{(k)}\} \quad (15)$$

which shows the term behavioral characteristics across all prediction tasks and time periods. This full behavioral profile is then given to the Behavioral Profiling Agent for showing and analyzing behavior over time

V. EXPERIMENTAL SETUP

The suggested architecture was developed as a web-based tool called "Social Media Archive Analysis Platform" that serves as an interface for displaying the information extracted and analyzed from the social media archives. The dashboard is divided into several analysis modules to facilitate the review of the profile information, behavior, interactions, communications, temporal activity, and content NLP-based features using a single interface. The primary interface also offers the possibility to refresh the analysis and upload a social media archive.

Profile overview module displays analyzed data about the user's account, which includes the username, profile name, biography, archive verification, account registration date, account age, website information, and other accounts related to this particular archive.

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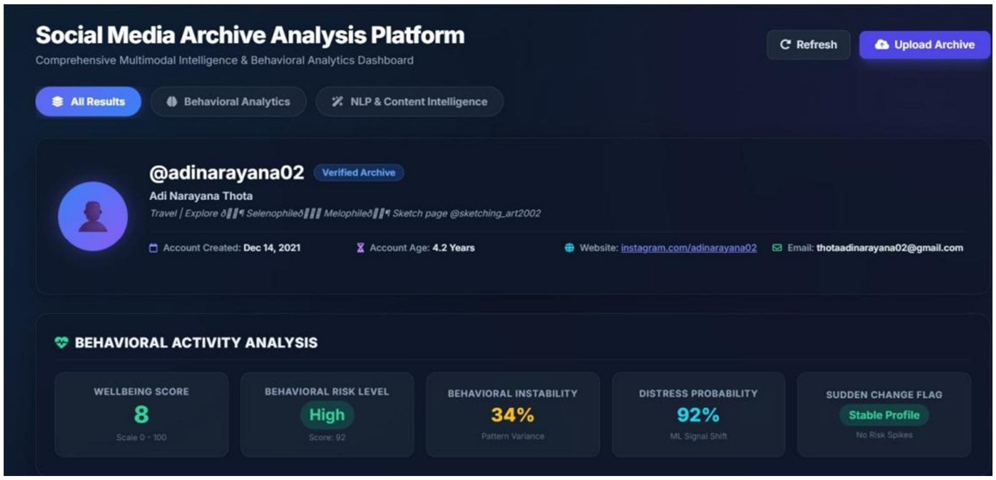

Fig2 : Profile overview and behavioral activity analysis interface

The Behavioral Activity Analysis module provides an overall view of the behavioral markers extracted from the processed archive. The module features wellbeing, behavioral risk, behavioral instability, distress probability, and abrupt change indicators. The module allows for obtaining a general view of the behavioral markers extracted in the course of analysis, before proceeding to analyzing individual behavioral markers in more detail.

The Interaction Pattern Analysis section highlights the interaction patterns of the user. Here we have information regarding follower/following ratio, engagement rate, and likes per post. Additionally, there is a breakdown of the media content, which is the representation of the proportion of different media contents in the form of photos, videos, reels, stories, audio, and documents. This is a visualization showing what type of content exists in the analyzed archive.

Fig3 : Interaction, communication, and temporal activity analysis dashboard.

The Communication Pattern Analysis section shows the summary of the communication activity in terms of the number of sent and received messages, as well as their ratio, and average message length. In addition, here is shown the top contacts interaction network based on the frequency of interaction between the contacts.

The Temporal Activity Analysis module analyzes the time-dependent aspects of user activity. The existing dashboard includes various metrics such as the late-night ratio, the most active day of the week, and the time window during which there is maximum user activity. It enables the analysis of activity behavior based on time windows. These outputs can be combined within the time windows of the longitudinal analysis used in the proposed framework – 3 months, 6 months, and 12 months.

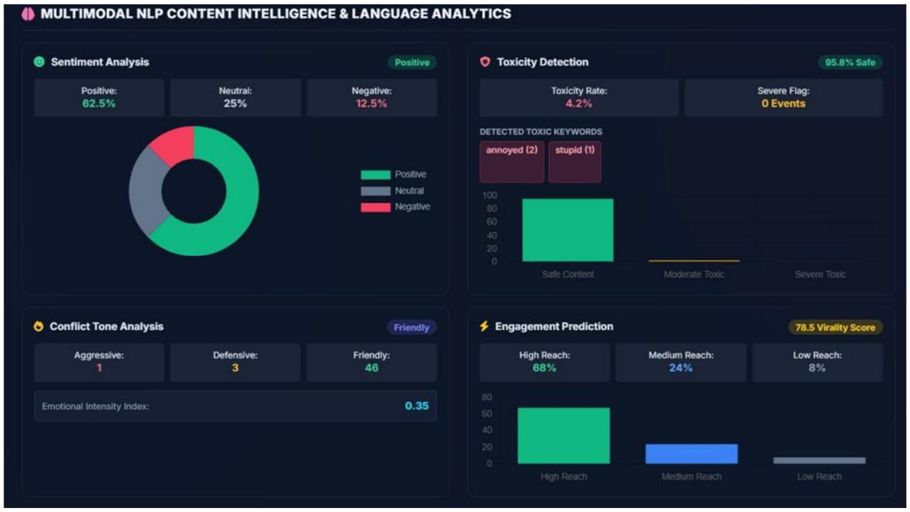

Fig4 : NLP content intelligence and language analytics dashboard.

The NLP Content Intelligence and Language Analytics section provides content analysis for the processed social media text. The developed interface includes Sentiment Analysis, Toxicity Detection, Conflict Tone Analysis, and Engagement Analysis. In the case of sentiment analysis, the ratio between positive, neutral, and negative content is displayed in numeric values and charts. The part related to toxicity indicates the toxicity level, signs of severe content, toxic keywords used, and the distribution of safe, moderately toxic, and severely toxic content.

Conflict Tone Analysis characterizes communication through three categories of aggression, defense, and friendliness along with the sign of the emotional intensity. That means that the system can not only display the general sentiment but also the tone of communication. The last component, which is called Engagement Analysis, provides the information about high, medium, and low levels of reach as well as the value related to virality.

Thus, the dashboard includes several analytical perspectives within one user interface. Instead of providing the results of classification for each separate NLP model, the dashboard provides links to the profile data, interaction behavior, communication patterns, temporal dynamics, content characteristics, sentiment, indicators associated with the toxicity level, conflict tone, and user engagement, allowing for a more general view of the social media archive.

The interface implemented is the visualization and decision-making layer of the suggested agent-based approach. The results of the archive processing, NLP, and temporal analysis are converted into charts, statistics, distributions, interaction and behavior models, which may be visualized via the dashboard interface

VI. RESULTS & DISCUSSION

The proposed Agent-Based Framework for Multilingual Social Media Behavior Analysis Using Multi-Task Transformer Learning was experimentally evaluated using publicly available benchmark datasets for sentiment analysis, emotion recognition, and hate speech detection. The objective of the evaluation was to assess the effectiveness of the shared XLM-RoBERTa encoder in learning multiple social media understanding tasks while maintaining high classification performance across different behavioral analysis objectives.

A. Sentiment Analysis Results:

The sentiment analysis module was evaluated using the TweetEval Sentiment benchmark, which consists of three sentiment categories: negative, neutral, and positive. The proposed XLM-R model achieved an overall accuracy of 69.15%, weighted precision of 69.49%, weighted recall of 69.15%, weighted F1-score of 69.12%, and Macro F1-score of 69.27%.

Class-wise evaluation demonstrates balanced performance across all sentiment categories. The negative class achieved the highest F1-score of 70.31%, followed by the positive class (69.25%) and the neutral class (68.26%). These results indicate that the proposed model effectively captures sentiment polarity in short social media posts despite the presence of informal language, abbreviations, and contextual ambiguity commonly found in online communication

Class	Precision	Recall	F1	Support
negative	0.6822	0.7253	0.7031	3972
neutral	0.7236	0.6461	0.6826	5936
positive	0.6442	0.7486	0.6925	2375

Table 1: Sentiment Analysis Results

B. Emotion Recognition Results:

Emotion recognition experiments were conducted using the TweetEval Emotion dataset containing four emotion categories: anger, joy, optimism, and sadness. The proposed XLM-R model achieved an overall accuracy of 79.96%, weighted precision of 79.96%, weighted recall of 79.96%, weighted F1-score of 79.90%, and Macro F1-score of 77.49%.

The confusion matrix demonstrates that most emotion samples were correctly classified, indicating the strong contextual understanding capability of the multilingual transformer model. Among the four emotion categories, anger achieved the highest classification performance with an F1-score of 85%, followed by joy (78%), sadness (76%), and optimism (71%). Most misclassifications occurred between the optimism and joy classes due to the semantic similarity between positive emotional expressions. Overall, the results confirm that XLM-R effectively learns contextual emotional representations from multilingual social media text.

Class	Precision	Recall	F1	Support
anger	0.8926	0.7742	0.8292	558
joy	0.7852	0.8575	0.8198	358
optimism	0.7188	0.5610	0.6301	123
sadness	0.6978	0.8220	0.7548	382

Table 2: Emotion Recognition Results

C. Hate Speech Detection Results

The hate speech detection module was evaluated using the TweetEval Hate dataset. The proposed framework achieved an overall accuracy of 83.07%, weighted precision of 83.12%, weighted recall of 83.07%, weighted F1-score of 83.09%, and Macro F1-score of 82.68%.

The classification report indicates balanced performance across both classes. The non-hate category achieved an F1-score of 85%, while the hate category obtained an F1-score of 80%, demonstrating the capability of the proposed model to accurately distinguish harmful content from normal social media conversations.

The generated Receiver Operating Characteristic (ROC) curve achieved an Area Under the Curve (AUC) of 0.898, indicating excellent discriminative capability. Furthermore, the Precision–Recall (PR) curve demonstrates stable precision across increasing recall values, confirming the robustness and reliability of the trained hate speech.

Class	Precision	Recall	F1	Support
non-hate	0.8665	0.1931	0.31	1714
hate	0.4648	0.5959	0.62	1252

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Table 3: Hate Speech Detection Results

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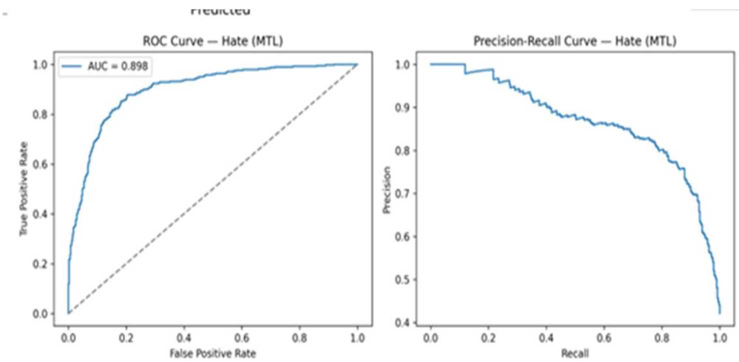

Fig 5 : ROC curve achieved an Area Under the Curve

D. *Comparative Performance Analysis*

Table IV summarizes the overall performance of the proposed XLM-R framework across all evaluated tasks. The highest performance was obtained for ambiguity and subjectivity of sentiment expressions in social media content.Overall, the experimental results demonstrate that transformer-based contextual representations are highly effective for multilingual social media behavior analysis. The shared multilingual XLM-R encoder successfully learns generalized semantic representations that can be adapted to multiple downstream tasks while maintaining competitive performance across different classification objectives. These findings validate the effectiveness of the proposed multi-task learning framework for behavioral understanding in multilingual social media environments.

	Accuracy	Precision	Recall	F1	Macro F1	Weighted F1	Support
Sentiment	0.6915	0.6949	0.6915	0.6912	0.6927	0.6912	12283
Emotion	0.7896	0.7981	0.7896	0.7896	0.7585	0.7896	1421
Hate	0.5165	0.6969	0.5165	0.4468	0.4710	0.4468	2966

Table 4 : Comparative Performance Analysis

VII. CONCLUSION

In this paper, we have suggested an agent-based pipeline for longitudinal social media behavior analysis based on XLM-RoBERTa transformer learning model. Data acquisition, archive processing, data structuring, multilingual pre-processing, behavior analysis, temporal aggregation, behavioral profiling and visualization modules are all included in the agent-based framework designed in the paper.The experimental evaluation has demonstrated the applicability of XLM-RoBERTa transformer model for important social media language analysis tasks. The model was able to achieve 69.15% accuracy and 69.27% Macro F1-score in sentiment analysis, whereas emotion recognition and hate speech detection models have shown the applicability of transformers for the purpose of social media text analysis. In addition, our framework allows for performing temporal aggregation using 3, 6 and 12-month analysis windows, which would allow for detecting changes and trends in behavioral indicators.The proposed architecture suggests a modular structure for incorporating various behavioral analysis tasks and representing their outputs in interactive dashboards, statistical reports, trend visualizations and longitudinal profiles.

Future works will include further expansion of the proposed framework in different ways. The first one includes integration of the individually trained sentiment, emotion and hate speech models into a multi-task framework based on a single XLM-RoBERTa transformer encoder with different prediction heads for each task. The comparative experiments involving the individual and multi-task frameworks could reveal advantages of the shared representation learning.

Secondly, the multilingual and code-mixed capabilities of the framework can be validated with multilingual and code-mixed datasets, which include regional languages and code-mixed samples. Other behavioral tasks, such as toxicity, distress, sarcasm, expression intensity, and engagement can be introduced after validation of the dataset.

Thirdly, the future works will involve exploration of different methods for improving the model's robustness and reproducibility, such as hyper-parameter optimization, class balancing, learning rate schedule, data augmentation and use of multiple random seeds. Advanced temporal modeling can also be considered in order to account for behavioral dynamics and long-term trends not limited by fixed 3-, 6-, and 12-month aggregation windows.

The system can be also extended to support archive processing in asynchronous and distributed way using database optimizations and caching techniques. The explainable AI approaches could be used in order to achieve more insights into linguistic and contextual determinants of model's predictions. Finally, privacy preserving processing, anonymization and access control measures need to be enhanced in order to make the analysis of social media behavior ethical.

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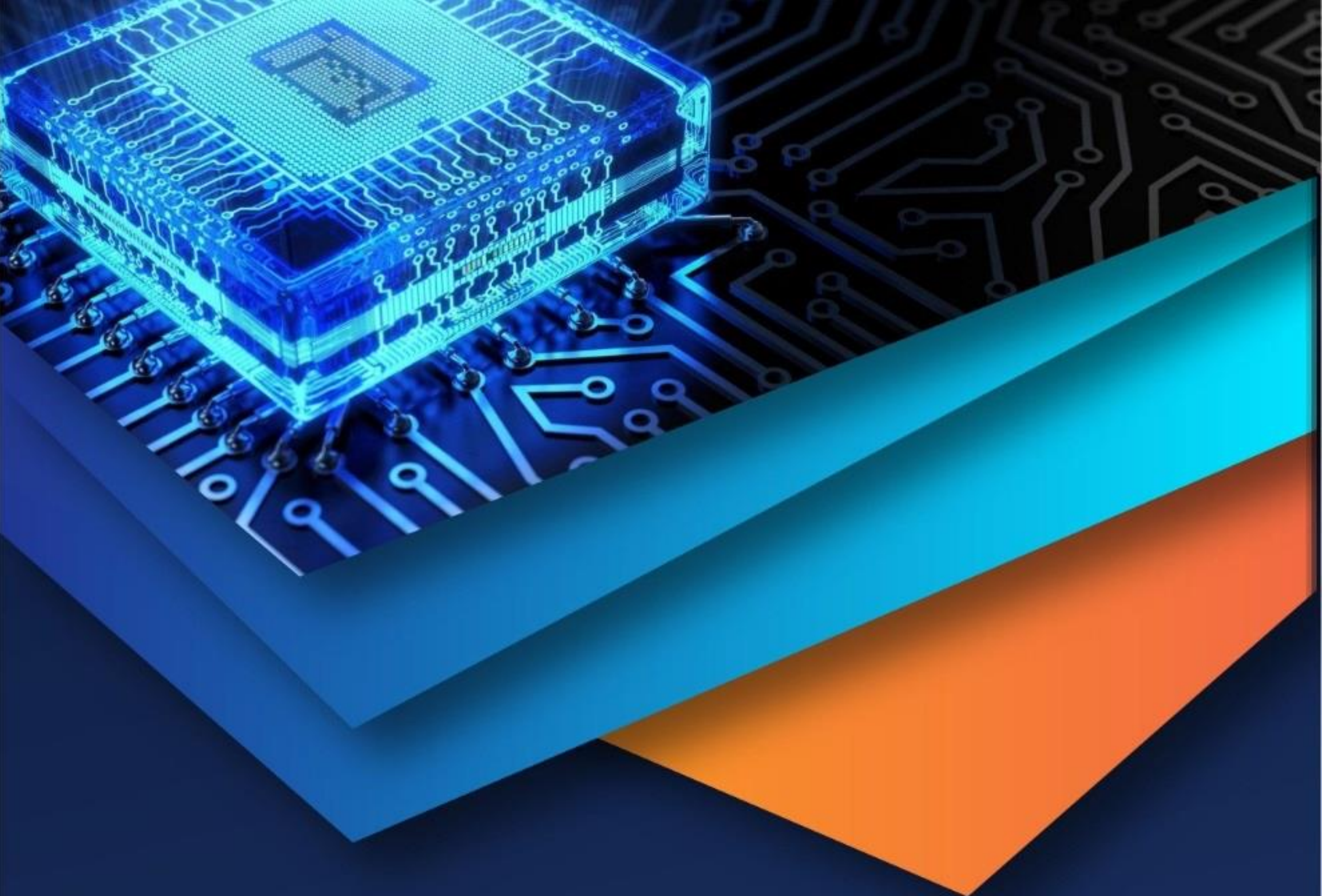

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