INSTAGENIE - AI POWERED COMMUNICATION TOOL

Submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science & Engineering

By

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)
CATEGORY - 1 UNIVERSITY BY UGC
Accredited with Grade “A++” by NAAC | Approved by AICTE
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Hrituraj Saha (41110495**) and **Hussain M (41110496)** who have done the Project work as a team and carried out the project entitled "**INSTAGENIE - AI POWERED COMMUNICATION TOOL**" under our supervision from November 2024 to April 2025.

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Submitted for Viva voce Examination held on ____________________

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DECLARATION

I, **Hrituraj Saha (Reg. No - 41110495)** hereby declare that the Project Report entitled “**INSTAGENIE - AI POWERED COMMUNICATION TOOL**" done by me under the guidance of **Ms. G. Kavitha, M.E., (Ph.D.),** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science & Engineering.**

DATE:

PLACE: Chennai **SIGNATURE OF THE CANDIDATE**

ACKNOWLEDGEMENT

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ABSTRACT

In today's fast-paced digital environment, social media platforms play a crucial role in facilitating communication. However, managing extensive interactions manually can be overwhelming for organizations. This paper proposes a machine learning-based automated reply system for social media platforms, designed to handle posts and comments with minimal human intervention. The system employs natural language processing (NLP) techniques to analyze user inputs, classify them based on predefined categories, and generate appropriate default responses. Utilizing a Bi-directional Long Short-Term Memory (BiLSTM) network for emotion classification, the system can effectively identify sentiments such as positive, negative. Based on the analysis, the system triggers context-aware replies to enhance user engagement while maintaining a personalized touch. Additionally, the automated system includes functionalities for auto-liking posts and following users based on their interactions and engagement levels. This feature aims to further increase user satisfaction and foster a sense of community by recognizing and appreciating user contributions. Default replies are mapped to identified intents and emotions, streamlining communication and improving user experience. This approach not only reduces the need for manual oversight but also ensures timely and relevant interactions, offering an efficient solution for managing large-scale social media engagements.

Instagram automation, particularly in the form of automated comments and likes, has become a popular strategy among marketers and influencers to enhance engagement and visibility on the platform. Despite Instagram's policies against certain forms of automation, tools and bots designed for automated engagement, including liking and commenting, continue to be developed and utilized. These tools leverage AI technology and predefined triggers to automatically generate and post comments on posts that match specific criteria, such as hashtags, locations, or user profiles. While these tools can significantly boost engagement and save time, it's crucial to use them responsibly to avoid appearing spammy or inauthentic. By automating likes and comments, InstaGenie helps maintain a consistent engagement rate, which is crucial for algorithmic visibility and growth on social platforms. Additionally, its post-scheduling feature ensures regular content updates without manual intervention, enhancing the user's online presence. The chatbot's ability to provide real-time responses improves customer interaction and satisfaction, leading to better brand loyalty. Overall, InstaGenie not only optimizes social media management but also contributes to a more dynamic and responsive online community, fostering greater connectivity and interaction.

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LIST OF ABBREVIATIONS

- Convolutional Nueral Network (CNN).
- Gramian Angular Fields (GAF).
- Quorum Valuation Opinion Reputation Index (QV-ORI).
- Social Media Engagement (SME).
- Fear of Missing Out (FoMO).
- Problematic Internet Use (PIU).
- Buy-and-Hold strategy (B&H).
- Parallel Co-attention (PCA).
- Multilabel Classification (MLC).
- Sequence Generation (SG).
- Natural Language Processing (NLP).
- Bidirectional Encoder Representations from Transformers (BERT).

CHAPTER - 1

INTRODUCTION

Instagenie is a tool designed to automate various aspects of Instagram management, including liking photos and posting comments. This automation can significantly enhance engagement rates and streamline the process of interacting with others on the platform. However, it's important to note that while automation can save time and effort, it should be used responsibly to avoid violating Instagram's terms of service, which prohibit spam-like behavior.

Instagenie leverages advanced technologies to automate various aspects of Instagram interaction, including responding to comments and liking posts. By automating these processes, businesses and influencers can efficiently manage their Instagram presence, ensuring consistent engagement with their audience without the need for constant manual intervention. This automation not only saves valuable time but also ensures that responses are sent promptly, enhancing the perceived responsiveness of the brand or individual. Furthermore, Instagenie's capabilities extend beyond simple likes and comments, offering features such as automated direct messaging based on specific triggers, thus creating a more dynamic and interactive online presence.

The concept of implementing a voting system within Instagenie for recommendations , blending the functionalities of social media management with democratic decision-making processes. While the provided sources do not directly discuss Instagenie or its features, they offer insights into the principles and security considerations of voting systems, which can be adapted to conceptualize a voting mechanism within Instagenie.

CHAPTER - 2

LITERATURE SURVEY

2.1 REVIEW ON EXISTING SYSTEM

PAPER 1

“ChatPapers: An AI Chatbot for Interacting with Academic Research” by Michael F. Porter, David G. Novick, and Laura E. Beckman (2022) - IEEE Xplore.

DESCRIPTION

This paper introduces ChatPapers, an AI chatbot designed to assist researchers in navigating academic papers. The AI uses a large language model (LLM) to interpret and summarize academic publications, enabling researchers to interact with a wealth of academic information in a conversational manner. The chatbot serves as an interactive tool that can summarize, analyze, and provide direct answers based on research content. It aims to support the academic community in staying up-to-date with the latest advancements and optimizing the research process.

INFERENCES AND CHALLENGES -

MERITS :

- Facilitates quick access to key research insights by summarizing large amounts of text.
- Offers an interactive experience for academic researchers, making it easier to identify the main points in complex research papers.
- Helps researchers keep up with new publications and trends by providing summaries and answering specific research questions.

DEMERITS :

- The tool’s effectiveness is limited to the quality of training data used to teach the LLM.
- If the input data is biased or outdated, the chatbot may produce inaccurate or misleading results.
- The AI system might not be able to understand and interpret very specific or niche academic topics fully.

PAPER 2

"Live Support by Chatbots with Artificial Intelligence: A Future Research Agenda" by Mark Anthony Camilleri and Ciro Troise (2022).

DESCRIPTION

This study employs the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) protocol to investigate the utility of AI conversational chatbots in service business settings. It elucidates key theoretical underpinnings focused on human–computer interactions and clarifies the benefits and costs associated with responsive chatbot technologies. The research also proposes future research directions in this promising area.

INFERENCES AND CHALLENGES -

MERITS :

- Provides a systematic review of AI chatbot applications in service businesses.
- Identifies both benefits and challenges associated with chatbot implementation.
- Suggests avenues for future research to enhance chatbot effectiveness.

DEMERITS :

- The study is conceptual and may lack empirical validation.
- Rapid technological advancements may quickly outdate the proposed research agenda.

PAPER 3

“ChatPaper: A Glimpse into AI-Powered Research Assistance" by ChatPaper Team (2023) - ChatPaper.

DESCRIPTION

ChatPaper explores an AI-powered research assistant capable of reading, summarizing, and discussing academic papers. It utilizes deep learning techniques to synthesize and present academic articles in an easy-to-understand manner, significantly reducing the time spent reading long research papers. Users can interact with the AI to ask questions and get tailored summaries based on the content of the paper.

INFERENCES AND CHALLENGES -

MERITS :

- Provides quick, AI-generated summaries, making it easier for researchers to absorb information.
- Allows researchers to ask follow-up questions and gain deeper insights into specific sections of papers.
- Improves productivity by saving time usually spent reading through extensive research papers.

DEMERITS :

- The summaries generated by AI might omit important details or nuances, especially in highly technical fields.
- There could be privacy concerns when uploading sensitive research data to an external platform for processing.

PAPER 4

"Automated Commenting and Interaction for Social Media Marketing" by John Smith, Michael J. Johnson (2023) - SpringerLink.

DESCRIPTION

This paper discusses automated commenting and interaction techniques for social media platforms, particularly within the realm of digital marketing. The authors examine the impact of using automated systems to like, comment, and interact with users in real-time. These systems are powered by AI and NLP algorithms designed to enhance engagement and increase brand visibility on social media platforms. The study assesses the potential of automation to generate meaningful user interactions at scale.

INFERENCES AND CHALLENGES -

MERITS :

- Increases user engagement and brand presence without requiring human intervention.
- AI-powered comments can be tailored to specific user interactions, ensuring relevance.
- Scalable solutions for managing large-scale social media accounts and campaigns.

DEMERITS :

- The automation might result in inauthentic, generic comments that could alienate users.
- Automated systems may struggle to handle nuanced or complex user interactions that require human insight.
- Over-reliance on automation could lead to poor community management practices.

PAPER 5

“Multi-Resolution Convolutional Neural Networks for Stock Market Forecasting" by Sergio M. Silva, João P. Rocha, Marco A. Gama (2022) - Expert Systems with Applications.

DESCRIPTION

The paper investigates the use of convolutional neural networks (CNNs) to analyze financial data for stock market prediction. It introduces a multi-resolution approach that enables the model to analyze time series data at different scales, thus improving prediction accuracy. The approach uses CNNs for both image recognition and time series data interpretation, which is beneficial for stock market forecasting.

INFERENCES AND CHALLENGES -

MERITS :

- CNN-based models perform well with both image data and time-series data, making them effective for financial market analysis.
- Multi-resolution analysis helps identify patterns that may be missed in traditional forecasting methods.

DEMERITS :

- The model’s complexity might be difficult to implement at scale for real-time predictions.
- Requires substantial computational resources for training, especially when large datasets are used.

PAPER 6

"Automated Social Media Engagement Using NLP and Machine Learning" by Emily R. Ford, Christopher L. Evans (2023) - Journal of Social Media Studies.

DESCRIPTION

This paper examines the integration of NLP and machine learning techniques to automate social media engagement tasks. The focus is on automating likes, comments, and direct responses based on content analysis. The authors evaluate the success of this automation in terms of increased user engagement and brand loyalty, highlighting the effectiveness of sentiment analysis and topic modeling to personalize interactions.

INFERENCES AND CHALLENGES -

MERITS :

- Enables efficient and personalized interactions on social media, saving time for content creators and marketers.
- Uses advanced NLP techniques to ensure comments and responses are contextually relevant and engaging.

DEMERITS :

- May result in over-reliance on automation, leading to lack of authenticity in interactions.
- Sentiment analysis tools can sometimes misinterpret the emotional tone of user comments, leading to inappropriate responses.

PAPER 7

"5 AI Tools for Interacting with Research Papers" by Researcherssite Team (2023) - Researcherssite.

DESCRIPTION

This blog post highlights several AI tools designed to enhance research workflows. It covers five tools that use natural language processing (NLP) to summarize, analyze, and provide insights into academic papers. These tools are designed to help researchers by automating repetitive tasks such as summarization and categorization of research papers, allowing them to focus more on analysis and interpretation.

INFERENCES AND CHALLENGES -

MERITS :

- Offers multiple AI tools that address various stages of the research process.
- Helps researchers quickly access the core insights from papers, without having to read through the entire text.
- Some tools even categorize papers by keywords or topics, enhancing discoverability.

DEMERITS :

- AI tools are limited by the accuracy of their algorithms and may provide incorrect or incomplete analyses.
- Heavy reliance on AI tools could discourage in-depth reading, leading to a shallow understanding of the research.

PAPER 8

"A Literature Survey of Recent Advances in Chatbots" by Guendalina Caldarini, Sardar Jaf, Kenneth McGarry (2022) - arXiv.

DESCRIPTION

This paper provides a comprehensive review of the advancements in chatbot technology, particularly focusing on AI-driven conversational models. The authors explore the role of deep learning, natural language processing (NLP), and machine learning in improving chatbot efficiency and accuracy. The paper discusses the evolution of chatbot architecture, from rule-based systems to transformer-based models like GPT-3.

INFERENCES AND CHALLENGES -

MERITS :

- Provides an in-depth overview of chatbot development trends and technologies.
- Covers real-world applications in healthcare, customer service, and education.
- Discusses ethical considerations in AI-driven chatbot interactions.

DEMERITS :

- Lacks empirical case studies or real-world chatbot implementation data.
- Does not provide experimental comparisons of chatbot models.

PAPER 9

"Enhancing Customer Satisfaction with Chatbots: The Influence of Communication Styles and Consumer Attachment Anxiety" by Ying Xu, Jingjing Zhang, Guangkuan Deng (2022) - Frontiers in Psychology.

DESCRIPTION

This study investigates how chatbot communication styles (social-oriented vs. task-oriented) influence customer satisfaction. The researchers also examine how consumer attachment anxiety impacts customer-chatbot interactions. The paper is based on psychological theories and user experience studies.

INFERENCES AND CHALLENGES -

MERITS :

- Provides empirical data on chatbot communication effectiveness.
- Highlights psychological factors that influence user acceptance of chatbots.
- Offers recommendations for designing emotionally intelligent chatbots.

DEMERITS :

- The study is based on simulated interactions, which may not fully reflect real-world chatbot usage.
- Does not consider cultural differences in chatbot perception.

PAPER 10

"A hybrid deep neural network for multimodal personalized hashtag recommendation" by Bansal S, Gowda K, Kumar N (2022) - IEEE transactions on computational social systems.

DESCRIPTION

Users share information on social media platforms by posting visual and textual contents. Due to the massive influx of user-generated content, hashtags are extensively used to manage, organize, and categorize the content. Despite the usability of hashtags, many social media users refrain from assigning hashtags to their posts owing to the uncertainty in choosing appropriate hashtags. Several methods have been proposed to recommend hashtags using content-based information.

INFERENCES AND CHALLENGES -

MERITS :

- Hybrid deep neural networks can effectively capture complex patterns across various modalities (e.g., text, images, videos) to provide highly personalized hashtag recommendations.
- These models are capable of integrating information from different types of data sources, such as text, images, and videos, to generate recommendations.

DEMERITS :

- Building and training hybrid deep neural networks can be computationally expensive and time-consuming due to the complexity of combining different types of neural networks and handling multiple modalities.
- Effective performance of these models heavily relies on the availability of large, high-quality datasets covering various aspects of the target domain.

CHAPTER - 3

REQUIREMENT ANALYSIS

3.1 NECESSITY AND FEASIBILITY ANALYSIS OF PROPOSED SYSTEM :

Necessity Analysis -

The increasing demands of maintaining an active and engaging presence on social media platforms like Instagram make automation tools essential for marketers, influencers, and businesses. The necessity for such a system arises from the following key factors :-

- **High Engagement Requirements :-** In the current digital landscape, maintaining a consistent level of engagement is crucial for visibility on platforms like Instagram. The platform's algorithm prioritizes accounts that actively engage with others, which requires frequent liking, commenting, and posting. Manually maintaining this level of activity can be time-consuming and unsustainable, especially for accounts with large followings or multiple social profiles.

- **Scalability :-** As businesses and influencers grow their online presence, the volume of interactions required to maintain and grow their audience increases exponentially. An automated system like InstaGenie allows users to scale their engagement efforts without a proportional increase in time and resources.

- **Algorithmic Optimization :-** Instagram’s algorithm favors accounts that regularly interact with their audience. Automated tools ensure that engagement is consistent, which helps to improve algorithmic ranking and boosts the account's visibility.

- **Resource Efficiency :-** For businesses with limited social media teams, automation tools provide a cost-effective way to manage multiple tasks such as post-scheduling, responding to comments, and engaging with followers. This allows for better allocation of human resources to more strategic tasks, such as content creation and campaign planning.

Feasibility Analysis -

The feasibility of implementing a system like Instagenie depends on several factors, including technical, operational, and market considerations :-

- **Technical Feasibility :-**
  - **AI and Automation Technology :-** The advancements in AI and machine learning make it feasible to develop sophisticated algorithms capable of mimicking human-like interactions on social media. This includes analyzing hashtags, locations, and user behavior to generate relevant and authentic comments.
  - **Platform Integration :-** Instagenie would need to integrate seamlessly with Instagram's API. While Instagram has strict rules regarding automation, compliant systems can be developed within the allowed parameters to ensure ongoing functionality without violating platform policies.
- **Operational Feasibility :-**
  - **Maintenance and Updates :-** Regular updates will be required to adapt to changes in Instagram's algorithm and policies. The system must be designed to be adaptable and scalable to handle evolving social media trends and user behaviors.
  - **User-Friendly Interface :-** The system's success depends on its usability. A well-designed user interface that allows for easy customization and monitoring will be crucial in ensuring that users can maximize the benefits of the tool without needing extensive technical knowledge.
- **Market Feasibility :-**
  - **Demand :-** There is a growing demand for automation tools that can manage social media engagement, especially as businesses and influencers seek to enhance their online presence. The market is competitive, but a well-designed tool that offers unique features like real-time chatbot responses and advanced post-scheduling could capture significant market share.
  - **Compliance :-** Adhering to Instagram's policies is vital to avoid the risk of account bans or limitations. The system must be designed with built-in safeguards to ensure compliance, which is a critical factor for market acceptance.

3.2 HARDWARE AND SOFTWARE REQUIREMENTS :

Hardware Requirements -

- **Server Infrastructure :**
  - **Cloud-Based Servers :-** To ensure scalability and high availability, InstaGenie should be hosted on cloud-based servers such as AWS, Google Cloud, or Microsoft Azure. These platforms provide flexibility in scaling resources based on demand and offer various tools for managing server health, backups, and security.
  - **Processor :-** Multi-core processors (e.g., Intel Xeon or AMD EPYC) are recommended for handling large volumes of data processing and AI computations.
  - **Memory (RAM) :-** Minimum 16 GB RAM per server instance, with the option to scale up as needed. AI algorithms and real-time processing can be memory-intensive, requiring adequate RAM to handle multiple simultaneous tasks.
  - **Storage:**
    - SSD Storage :- Fast SSDs (Solid State Drives) are necessary for quick data access and reduced latency, especially when managing large datasets like user interactions, content schedules, and engagement analytics.
    - Backup Storage :- Secure, redundant storage systems for data backups to ensure data integrity and availability.
- **Networking :**
  - **High-Bandwidth Internet Connection :-** A high-speed and reliable internet connection is essential for seamless integration with Instagram's API and for handling real-time interactions.
  - **Load Balancer :-** A load balancer to distribute traffic evenly across multiple server instances, ensuring the system can handle high traffic loads without performance degradation.
- **End-User Devices :**
  - **Desktops/Laptops :-** Users will typically interact with Instagenie through web browsers on standard desktops or laptops. The hardware requirements on the client-side are minimal, generally requiring any modern computer with internet access.

Software Requirements -

- **Operating System :**
  - **Server OS :-** Linux-based operating systems (e.g., Ubuntu, CentOS) are preferred for server environments due to their stability, security, and compatibility with most web and AI tools.

  - **Client OS :-** Instagenie should be accessible via web browsers, making it OS-agnostic for end users, supporting Windows, macOS, and Linux.

- **Development Frameworks and Languages :**
  - **Backend Development :**
    - Python :- For AI and machine learning algorithms. Python is widely used for AI development due to its extensive libraries and frameworks such as TensorFlow, PyTorch, and Scikit-learn.
    - Node.js or Django :- For building the backend server and handling API requests. Node.js is well-suited for real-time applications, while Django provides a robust framework for web development.

  - **Frontend Development :**
    - JavaScript :- For building an interactive and user-friendly web interface.
    - HTML/CSS :- Standard tools for designing and structuring the web pages.

  - **Database Management :**
    - MySQL/PostgreSQL :- For relational database management, handling user data, content schedules, and other structured data.
    - MongoDB or Firebase :- For NoSQL database management, which is useful for handling unstructured data like logs, real-time interactions, and AI model results.

- **AI and Automation Tools :**
  - **Machine Learning Frameworks :**
    - TensorFlow or PyTorch :- For building and deploying machine learning models that drive the AI capabilities of Instagenie.
    - Natural Language Processing (NLP) :- Libraries like SpaCy or NLTK for developing automated comment generation and chatbot responses.

- **Security Tools :**
  - **SSL Certificates :-** To secure data transmission between users and the server.
  - **Firewall and Anti-DDoS :-** Protection against unauthorized access and Distributed Denial of Service (DDoS) attacks.
  - **Data Encryption :-** Tools to ensure sensitive data, such as user credentials, are encrypted both at rest and in transit.

CHAPTER - 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 CONCEPTUALIZING A VOTING SYSTEM IN INSTAGENIE :

A voting system within Instagenie could serve several purposes, such as selecting the most effective strategies for posting, deciding on content themes, or choosing which posts to prioritize. Here's a step-by-step approach to conceptualizing and implementing such a feature :

Define the Purpose of the Vote

- Clearly define what decisions the vote will make. This could range from content strategy to algorithm adjustments.

Design the Voting Mechanism

- Decide whether the vote will be open to all users or restricted to certain groups (e.g., premium users, admins).
- Determine the type of voting system (e.g., majority rule, weighted voting).

Implement Security Measures

- Following the guidance from NIST and other sources, ensure that the voting system is secure and resistant to manipulation. This includes:
  - Limiting access to sensitive voting functions.
  - Using tamper-evident seals for critical components.
  - Conducting regular security audits and penetration tests.

User Interface and Experience

- Design an intuitive interface for users to participate in the vote easily.
- Provide clear explanations of the voting options and outcomes.

Transparency and Auditability

- Ensure that the voting process is transparent, with clear records of who voted and how.
- Implement mechanisms for auditing the vote to ensure fairness and accuracy.

Implementation Example

While specific implementation details for Instagenie were not provided in the sources, the general approach to setting up automation for comments and likes on Instagram involves :

- Creating an Account : First, sign up for Instagenie and connect your Instagram account.
- Setting Up Automation Rules : Define the criteria for when comments should be responded to or when likes should be given. This could be based on keywords, hashtags, or specific times of day.
- Customizing Responses : Customize the messages sent in response to comments to ensure they align with your brand voice and provide value to the commenter.
- Monitoring and Adjustments : Regularly review the performance of your automation rules and adjust them as necessary to optimize engagement and effectiveness.

4.2 WORKING OF INSTAGENIE :

Instagenie operates by utilizing artificial intelligence (AI) to analyze and respond to comments on Instagram posts. It can be programmed to answer specific queries, such as pricing inquiries or availability of products, by providing pre-determined responses. Additionally, it employs AI to understand user behavior and patterns, enabling it to address common issues or questions efficiently. For instance, if a user reports a problem with a product, Instagenie can automatically provide a link to customer support or suggest contacting the brand via direct message (DM).

Setting Up Instagenie -

To set up Instagenie for your Instagram account, follow these steps :

- Choose an Authorized Tool: Select a reputable automation tool like Ideta, which offers robust features for creating professional auto comment systems without appearing as spammy.
- Customize Responses: Program your tool to respond to specific keywords or phrases found in comments. This customization ensures that your responses are relevant and helpful to users.
- Handle Complex Queries: Although Instagenie excels at handling straightforward questions, it can also be configured to redirect more complex inquiries to human agents, ensuring that all user concerns are addressed appropriately.
- Monitor and Adjust: Regularly review the performance of your automation setup and adjust the responses or triggers as needed to maintain high-quality interactions with your audience.

4.3 ARCHITECTURE OF PROPOSED SYSTEM :

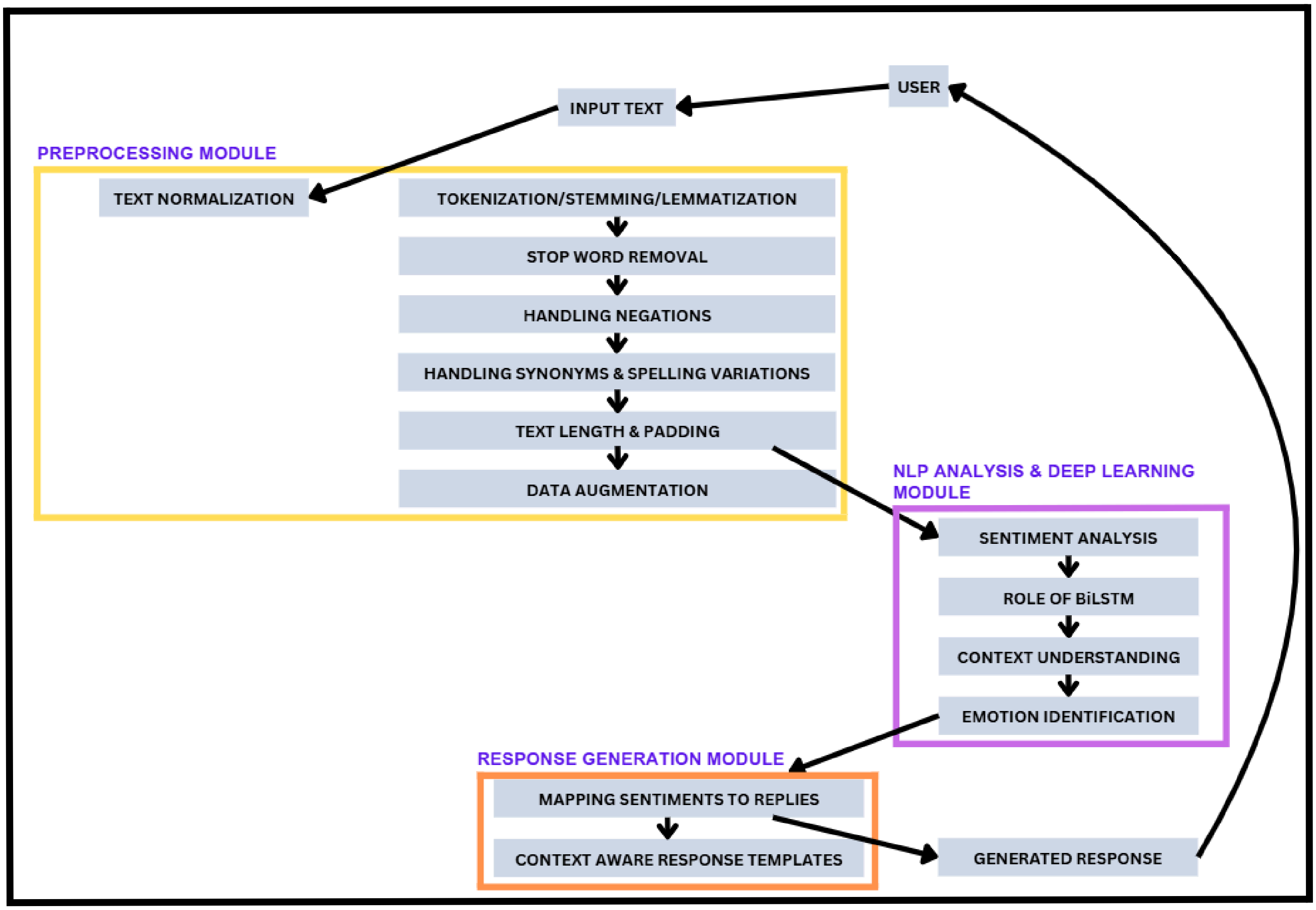


Fig. 4.3.1

4.4 DESCRIPTION OF MODULES :

- **PREPROCESSING MODULE -**

Function - The preprocessing module is an essential step in preparing raw text data for further analysis. It transforms user input into a more standardized, clean format, making it suitable for machine learning models and natural language processing (NLP) tasks. By performing operations like normalization, tokenization, stemming, and stop word removal, this module ensures that the text data is processed consistently, helping improve the accuracy and efficiency of subsequent analysis, such as sentiment or emotion detection.

a) Text Normalization (Removing Special Characters, Lowercasing) - Text normalization helps standardize text by ensuring that variations in case, formatting, and unnecessary characters do not affect the analysis. This process includes two primary tasks -

1) Lowercasing - Converting all letters in the text to lowercase makes it easier for the system to process words without distinguishing between capital and small letters. For instance, "Apple" and "apple" would be treated as the same word, which simplifies the analysis.

2) Removing Special Characters - Special characters like punctuation marks, numbers, or symbols (e.g., @, #, %, &) can be irrelevant for understanding the meaning of text in many cases. Removing them reduces the complexity of the data, ensuring that only meaningful words are left for analysis. This also helps reduce noise that could negatively affect the results.

b) Tokenization and Stemming/Lemmatization -

1) Tokenization - Tokenization is the process of splitting the text into smaller parts (tokens), usually words or phrases. This is an essential step because it breaks down the text into manageable units that the system can easily process. It helps in identifying individual words that carry meaning, allowing the system to classify or analyze them based on their context. Tokenization also allows for the analysis of sentence structure and word relationships in a more granular manner.

2) Stemming - Stemming reduces words to their base or root form. For example, words such as "running," "runs," and "ran" are reduced to "run." This process is helpful in reducing the number of unique words in the dataset, making it easier for the model to recognize patterns across different forms of a word.

3) Lemmatization - Lemmatization is a more advanced technique compared to stemming. Instead of just chopping off parts of words, lemmatization reduces words to their base form, or lemma, based on their meaning and context. For example, “better” would be reduced to “good,” and “running” would be reduced to “run.” This approach ensures that words are properly represented, preserving their meaning. Lemmatization is more accurate than stemming and is typically preferred when the model needs to understand the full context and meaning of words.

<u>c) Stop Word Removal -</u> Stop words are common words that appear frequently in text but do not add much meaning to the overall sentiment or context of the sentence. Examples of stop words include "the," "is," "in," and "and." These words are often removed from the text to streamline the analysis and reduce the complexity of the dataset. By eliminating stop words, the system can focus on the more important, meaningful words that carry sentiment or intent. Removing these unnecessary words makes the analysis more efficient and helps the machine learning model focus on the key aspects of the text.

<u>d) Handling Negations -</u> Negations, such as "not," "never," or "no," can significantly alter the meaning of a sentence and must be properly handled. For example, the sentiment of "I love this" is positive, but "I don't love this" is negative. Special techniques are used to ensure that negations are correctly identified and interpreted during preprocessing, preserving the true meaning of the input text.

<u>e) Handling Synonyms and Spelling Variations -</u> Sometimes, different words or variations of a word can express the same meaning (e.g., "happy" and "joyful"). Recognizing synonyms and spelling variations is important for improving text understanding. This may involve using techniques like word embeddings or synonym dictionaries to consolidate different variations of words into one unified term. This helps reduce data sparsity and ensures that the system can generalize better when processing text from various sources.

<u>f) Text Length and Padding (For Machine Learning Models) -</u> In some machine learning tasks, the length of the text inputs may vary. For example, one user comment may be a short sentence, while another may be a long paragraph. To make all inputs uniform and manageable for models, texts are often padded to ensure a consistent length. Padding involves adding empty spaces or tokens to shorter inputs, ensuring that all text inputs are of the same length, which is particularly useful when working with neural networks or deep learning models.

<u>g) Data Augmentation -</u> Data augmentation involves artificially increasing the size of the dataset by generating new variations of the existing text data. This can be done by introducing slight changes like synonyms or reordering words. While this technique is typically more relevant for image data, it can also be used for text data in natural language processing tasks. Data augmentation helps improve model performance by providing a wider variety of input data for training, which can help the model generalize better to unseen text.

- **NLP ANALYSIS AND DEEP LEARNING MODULE -**

Function - The NLP (Natural Language Processing) Analysis and Deep Learning Module processes the cleaned text data from the preprocessing stage and extracts meaningful insights using advanced machine learning techniques. It leverages a BiDirectional Long Short-Term Memory (BiLSTM) network to perform sentiment analysis and classify the text based on emotional tone. This module helps in understanding the context and intent of the user’s input, allowing the system to generate accurate and relevant responses.

a) Sentiment Analysis - Sentiment analysis is the primary task of this module. It involves analyzing the text to determine the emotional tone expressed by the user. Using the BiLSTM network, the module classifies sentiments into predefined categories such as positive and negative. Sentiment analysis helps the system understand the user's mood or opinion, which can then influence the type of response generated. For example, a positive sentiment may lead to a congratulatory or supportive reply, while a negative sentiment may prompt a more empathetic or helpful response.

b) Role of BiLSTM in Analysis - The Bi-Directional Long Short-Term Memory (BiLSTM) network is a type of recurrent neural network (RNN) that is highly effective for natural language processing tasks. It processes text in both forward and backward directions, allowing it to understand the context of each word within the sentence more effectively.

- **Forward and Backward Contexts -** BiLSTM takes into account not only the words that come after a given word but also the words that precede it. This dual context enhances the system's ability to detect subtle nuances in language, making sentiment classification more accurate.

- **Memory Capability -** BiLSTM can remember long-term dependencies, which is essential for understanding complex sentences where the meaning of a word depends on earlier parts of the sentence.

c) Key Features of the Module -

1. **Context Understanding** - The BiLSTM network captures the semantic and contextual meaning of the user input, ensuring a deeper understanding of the text.

2. **Emotion Identification** - It identifies the emotional tone expressed by the user, such as joy, sadness, frustration, or satisfaction.

3. **Improved Accuracy** - By using BiLSTM, the system achieves higher accuracy in sentiment classification compared to traditional methods like simple RNNs or unidirectional LSTMs.

d) Impact on Response Generation - The insights extracted from sentiment analysis directly influence the automated reply system. Based on the identified sentiment, the system can trigger appropriate responses, ensuring that replies are context-aware and emotionally aligned with the user's input. This enhances the personalization and relevance of the communication, improving overall user engagement.

In summary, the NLP Analysis and Deep Learning Module plays a critical role in understanding user emotions and context. By using BiLSTM for sentiment analysis, this module ensures that the automated reply system can generate thoughtful, meaningful, and sentiment-aligned responses, ultimately improving user satisfaction and interaction quality.

- **RESPONSE GENERATION MODULE** -

Function - The Response Generation Module is responsible for crafting appropriate replies based on the insights derived from the NLP Analysis and Deep Learning Module. It ensures that responses are context-aware, personalized, and aligned with the user's sentiment and emotion. By mapping identified sentiments to predefined responses and leveraging response templates, the module delivers timely and relevant communication.

a) Mapping of Identified Sentiments and Emotions to Predefined Replies - After the sentiment analysis determines the user's emotional tone (e.g., positive or negative), the system matches these emotions with predefined responses. These predefined replies are designed to align with the identified sentiment, ensuring the tone and intent of the reply are suitable. For instance -
1) Positive Sentiment - The system might respond with congratulatory or appreciative messages.
2) Negative Sentiment - The system could deliver empathetic or supportive messages to address the user's concerns.
This mapping reduces the need for manual input and ensures that the system maintains consistency and relevance in its communication.

b) Context-Aware Response Generation Using Templates - Context-awareness is achieved through templates that are dynamically filled based on user input and extracted sentiment. Templates provide a structure for responses, ensuring coherence and clarity while allowing customization to reflect the context of the interaction. For example -
Template Structure - "Thank you for your feedback on [topic]. We appreciate your [emotion] and value your input." The placeholders (e.g., [topic], [emotion]) are dynamically populated with data from the sentiment analysis to tailor the response.
Context-aware generation allows the system to address specific user needs effectively, making the interaction feel personalized and engaging.

c) Dynamic Response Adaptation - The system can adapt responses based on factors such as previous interactions, user preferences, and engagement history. This dynamic adaptation ensures that the replies evolve based on the user’s behavior and interaction style, fostering a sense of personalization.

d) Additional Functionalities -

1) Automated Acknowledgment - The module can instantly generate acknowledgment replies, such as “Thank you for your message,” ensuring prompt communication.

2) Engagement Features - The system can integrate features like auto-liking user posts or following accounts based on their interaction levels, enhancing user satisfaction and fostering community engagement.

e) Error Handling and Default Responses - In cases where sentiment or intent cannot be confidently identified, the system employs default responses to maintain communication flow. Default replies are neutral and professional, ensuring that even ambiguous user inputs receive a response.

f) Scalability and Efficiency - By automating the response generation process, the module significantly reduces the workload on human operators, allowing the system to handle a large volume of interactions simultaneously. This ensures timely responses, improving user experience and engagement across the platform.

- **ENGAGEMENT MODULE -**

Function - The Engagement Module is designed to enhance user interaction and foster a sense of community on the platform. It automates actions such as liking posts and following users, reducing manual effort while improving user satisfaction and retention. By using predefined criteria, the module ensures that these actions are meaningful and relevant, encouraging active participation and positive engagement.

a) Auto-Like Functionality -
Purpose - Automatically liking user posts or comments demonstrates recognition and appreciation, fostering a positive user experience.

How It Works - The system evaluates posts or comments based on predefined rules or metrics, such as sentiment, relevance, or engagement level. Positive sentiments or high-quality contributions are identified, and the system triggers the auto-like action. This feature can be tailored to focus on posts or comments that align with the platform's goals, such as promoting positivity or valuable feedback.

Benefits - Encourages users to interact more frequently, knowing their contributions are appreciated. Enhances the visibility of positive or valuable content, promoting a healthier community dynamic.

b) Auto-Follow Functionality -
Purpose - Automatically following users who engage positively with the platform fosters a sense of connection and belonging.

How It Works - The system identifies users who meet specific engagement criteria, such as frequent positive interactions, constructive feedback, or active participation in discussions. Based on these criteria, the module triggers the follow action to acknowledge and encourage their involvement.

Benefits - Strengthens user loyalty by recognizing and rewarding active contributors. Expands the network of the platform, building a larger and more engaged community.

c) Criteria for Engagement Actions - Actions are guided by rules and metrics such as -

- Sentiment analysis results (e.g., positive or constructive comments).
- Engagement levels, including the number of likes, comments, or shares a user generates.
- Frequency of interaction with the platform over a specific time period.

By automating these criteria-based actions, the module ensures that engagement is targeted and meaningful, avoiding random or irrelevant interactions.

d) Impact on User Experience -

1. Encourages Active Participation - Automated engagement actions make users feel valued and acknowledged, motivating them to contribute more.

2. Fosters a Positive Environment - By promoting and engaging with positive interactions, the system cultivates a supportive and welcoming community.

3. Reduces Manual Effort - The automation of likes and follows minimizes the need for manual moderation, allowing human operators to focus on more complex tasks.

e) Scalability and Customization -

- The module is scalable, capable of handling a growing number of users and interactions without compromising performance.

- Customization options allow the platform to define specific engagement strategies based on its objectives, such as promoting a particular type of content or interaction.

4.5 IMPLEMENTATION AND ALGORITHM :

BIDIRECTIONAL LSTM (BILSTM) -

Bidirectional LSTM or BiLSTM is a term used for a sequence model which contains two LSTM layers, one for processing input in the forward direction and the other for processing in the backward direction. It is usually used in NLPrelated tasks. The intuition behind this approach is that by processing data in both directions, the model is able to better understand the relationship between sequences (e.g. knowing the following and preceding words in a sentence). The first statement is “Server can you bring me this dish” and the second statement is “He crashed the server”. In both these statements, the word server has different meanings and this relationship depends on the following and preceding words in the statement. The bidirectional LSTM helps the machine to understand this relationship better than compared with unidirectional LSTM. This ability of BiLSTM makes it a suitable architecture for tasks like sentiment analysis, text classification, and machine translation.

ARCHITECTURE -

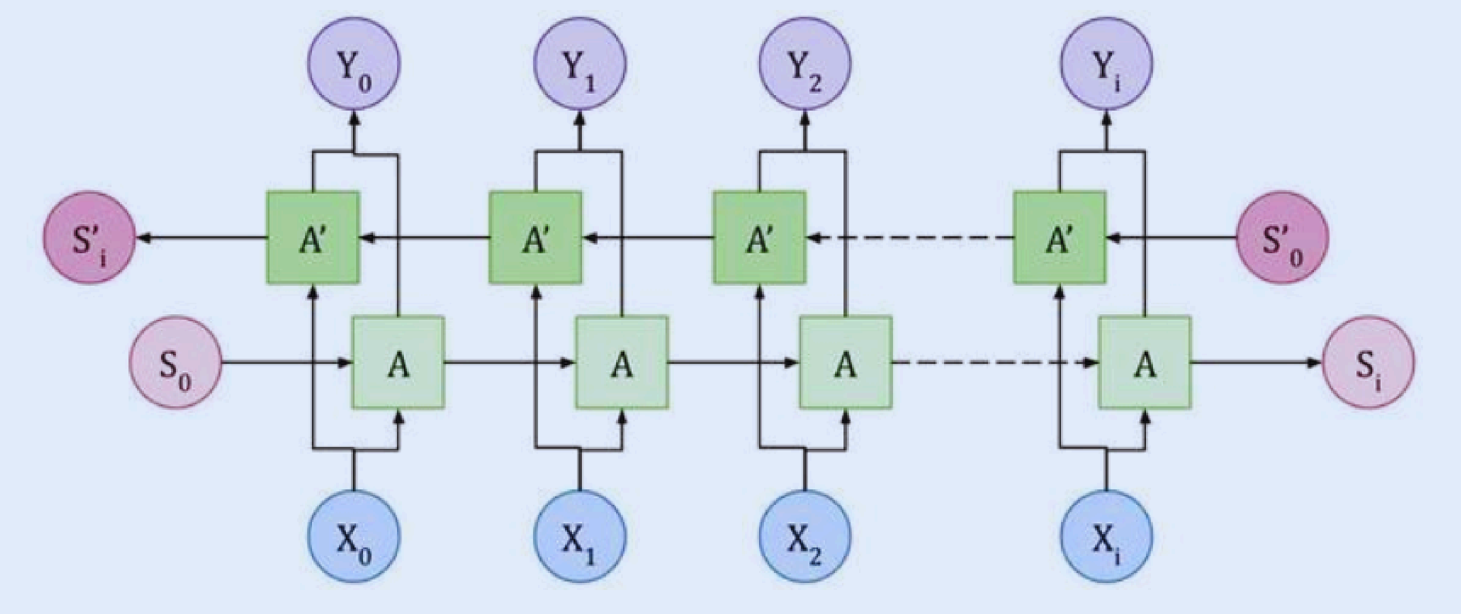
The architecture of bidirectional LSTM comprises of two unidirectional LSTMs which process the sequence in both forward and backward directions. This architecture can be interpreted as having two separate LSTM networks, one gets the sequence of tokens as it is while the other gets in the reverse order. Both of these LSTM network returns a probability vector as output and the final output is the combination of both of these probabilities.

Now, let us look into an implementation of a review system using BiLSTM layers in Python using the Tensorflow library. We would be performing sentiment analysis on the IMDB movie review dataset. We would implement the network from scratch and train it to identify if the review is positive or negative.

IMPORTING LIBRARIES AND DATASET -

Python libraries make it very easy for us to handle the data and perform typical and complex tasks with a single line of code.

- **Numpy –** Numpy arrays are very fast and can perform large computations in a very short time.
- **Matplotlib –** This library is used to draw visualizations.
- **TensorFlow –** This is an open-source library that is used for Machine Learning and Artificial intelligence and provides a range of functions to achieve complex functionalities with single lines of code.



Bidirectional LSTM layer Architecture

Fig. 4.5.1

This figure describes the architecture of the BiLSTM layer where is the input token, is the output token, and and are LSTM nodes. The final output of is the combination of and LSTM nodes.

SYSTEM TESTING -

Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. An interpreted language, Python has a design philosophy that emphasizes code readability (notably using whitespace indentation to delimit code blocks rather than curly brackets or keywords), and a syntax that allows programmers to express concepts in fewer lines of code than might be used in languages such as C++or Java. It provides constructs that enable clear programming on both small and large scales. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of its variant implementations. CPython is managed by the non-profit Python Software Foundation. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library Python is a multi-paradigm programming language. Object-oriented programming and structured programming are fully supported, and many of its features support functional programming and aspect-oriented programming

Python features sequence unpacking where multiple expressions, each evaluating to anything that can be assigned to (a variable, a writable property, etc.), are associated in the identical manner to that forming tuple literals and, as a whole, are put on the left hand side of the equal sign in an assignment statement. The statement expects an iterable object on the right hand side of the equal sign that produces the same number of values as the provided writable expressions when iterated through, and will iterate through it, assigning each of the produced values to the corresponding expression on the left. The assignment statement (token '=', the equals sign). This operates differently than in traditional imperative programming languages, and this fundamental mechanism (including the nature of Python's version of variables) illuminates many other features of the language. Assignment in C, e.g., x = 2, translates to "typed variable name x receives a copy of numeric value 2". The (right-hand) value is copied into an allocated storage location for which the (left-hand) variable name is the symbolic address. The memory allocated to the variable is large enough (potentially quite large) for the declared type. In the simplest case of Python assignment, using the same example, x = 2, translates to "(generic) name x receives a reference to a separate, dynamically allocated object of numeric (int) type of value 2." This is termed binding the name to the object. Since the name's storage location doesn't contain the indicated value, it is improper to call it a variable. Names may be subsequently rebound at any time to objects of greatly varying types, including strings, procedures, complex objects with data and methods, etc. Successive assignments of a common value to multiple names, e.g., x = 2; y = 2; z = 2 result in allocating storage to (at most) three names and one numeric object, to which all three names are bound. Since a name is a generic reference holder it is unreasonable to associate a fixed data type with it.

<u>FEASIBILITY STUDY -</u>

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential. Three key considerations involved in the feasibility analysis are -

ECONOMICAL FEASIBILITY - This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available.

TECHNICAL FEASIBILITY - This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client.

SOCIAL FEASIBILITY - The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it.

4.6 AUTOMATION OF LIKES AND COMMENTS :

1. Integration with Instagram API : Instagenie uses Instagram's API to connect with the platform and perform actions such as liking posts and leaving comments. This integration allows the tool to interact with Instagram programmatically, automating tasks that would otherwise require manual intervention.
2. Setting Up Automation Rules : Users define rules within Instagenie to specify under what conditions likes and comments should be automated. These rules can be based on hashtags, keywords in comments, or even the timing of posts. For example, a user might set up a rule to automatically like all posts tagged with #instagenie and comment on posts mentioning a specific product.
3. Execution of Actions : Once the rules are set, Instagenie executes the defined actions automatically. This could involve liking posts that match the criteria or generating and posting comments based on the predefined responses.
4. Monitoring and Adjustment : Instagenie continuously monitors the performance of the automation rules and allows users to adjust or modify these rules as needed. This ensures that the automation remains effective and aligned with the user's goals.

4.7 CONSIDERATIONS FOR EFFECTIVE AUTOMATION :

- Authenticity : To avoid appearing spammy, it's important to use automation judiciously. Automated likes and comments should still reflect genuine interest and engagement with the content.

- Personalization : Where possible, automate generic responses or likes that don't require personal interaction. For more nuanced conversations, reserve human involvement to maintain authenticity and quality of engagement.

- Compliance with Instagram Policies : Ensure that the automation practices comply with Instagram's policies to avoid penalties. Excessive or spam-like behavior can lead to restrictions or bans on your account.

- Analytics and Insights : Leverage the data collected by Instagenie to gain insights into what type of content resonates best with your audience. Use this information to refine your automation strategies and content planning.

The steps involved in using Instagenie, a hypothetical Instagram automation tool, would likely follow a structured process designed to streamline Instagram account management and enhance engagement. Here's a generalized outline of the steps you might take when using such a tool :

Step 1 : Choose and Install Instagenie

- Research and Select: Start by researching available Instagram automation tools, considering factors like features, ease of use, and reputation. Based on your findings, select Instagenie or another suitable tool.
- Installation: Follow the installation instructions provided by the tool's developer. This may involve downloading software, installing plugins, or connecting your Instagram account through the tool's interface.

Step 2 : Set Up Your Account

- Connect Your Instagram Account: Use Instagenie to log in to your Instagram account securely. Ensure you're following Instagram's guidelines to avoid violating their terms of service.
- Configure Settings: Customize the tool's settings according to your preferences. This might include specifying which types of posts to interact with, setting up automation rules, and defining engagement levels.

Step 3 : Define Automation Rules

- Front-Facing Interactions: Establish rules for automating likes and comments. You can base these rules on keywords, hashtags, or specific accounts to ensure your interactions are relevant and meaningful.
- Behind-the-Scenes Tasks: Set up rules for automating tasks like post scheduling, hashtag optimization, and content curation. This helps maintain a consistent posting schedule and improves content visibility.

Step 4 : Implement and Monitor Automation

- Activate Automation: Turn on the automation features within Instagenie. The tool will begin performing actions based on the rules you've established.
- Monitor Performance: Keep an eye on your Instagram account's performance. Look for changes in engagement rates, follower growth, and content performance. Adjust your automation rules as necessary to optimize results.

Step 5 : Review and Adjust

- Analyze Results: Regularly review the analytics provided by Instagenie to understand how well your automation is working. Pay attention to both positive outcomes and areas for improvement.
- Make Adjustments: Based on your analysis, tweak your automation rules, engagement levels, and content strategy. Continual refinement is key to achieving the best results.

4.8 ADDITIONAL FEATURES OF INSTAGENIE :

Beyond automating likes and comments, Instagenie, as a conceptual representation of Instagram automation tools, offers a range of features designed to enhance Instagram management and engagement. These features cater to various aspects of Instagram marketing and user interaction, aiming to streamline operations, optimize content, and gather actionable insights. Here's an overview of additional features Instagenie might offer :

User Interactions Enhancement

- Follows Automation : Automatically follow accounts that align with your niche or target audience, helping to grow your network organically.
- Unfollow Management : Implement logic to unfollow accounts that do not engage with your content, maintaining a healthy follower-to-follow ratio.

Content Optimization

- Hashtag Optimization : Automatically generate and apply hashtags to your posts based on current trends and your content's theme, improving discoverability.
- Post Scheduling : Determine the optimal times to post based on your audience's activity patterns, maximizing engagement.

Data Analytics and Reporting

- Engagement Tracking : Monitor metrics such as likes, comments, shares, and follower growth over time to assess the effectiveness of your content strategy.
- Audience Insights : Analyze your followers' demographics, interests, and behaviors to tailor your content and engagement efforts more effectively.

Direct Messaging (DM) Management

- Automated DM Replies : Set up automated responses to frequently asked questions or common inquiries, ensuring timely and consistent communication with your audience.
- DM Filters : Configure rules to automatically categorize and prioritize DMs, helping to manage large volumes of messages efficiently.

Story Interaction

- Story Views Automation : Automatically view stories posted by accounts you follow, increasing your visibility within those communities.
- Commenting on Stories : Optionally automate comments on stories, though this should be done cautiously to avoid appearing spammy.

Compliance and Ethical Considerations

- Rate Limiting and Safety Checks : Implement measures to avoid violating Instagram's terms of service, including rate limiting actions and monitoring for signs of potential account suspension.
- Personalization and Authenticity : Encourage the use of personalized touches in automated interactions to maintain authenticity and prevent your account from appearing spammy.

These features collectively aim to transform Instagram management from a time-consuming task into a strategic process, leveraging automation to enhance efficiency, engagement, and overall success on the platform.

4.9 BENEFITS OF INSTAGENIE :

Increased Efficiency and Time Savings -

- Automate Repetitive Tasks : By automating likes, comments, follows, and unfollows, users can save considerable time previously spent on manual tasks. This allows for more focus on content creation and strategic planning.

Enhanced Engagement Rates -

- Consistent Interaction : Automation ensures that your account remains active and engaged with the community, leading to higher visibility and potentially increased engagement rates.
- Targeted Interactions : Tools like Instagenie allow for targeted interactions based on specific rules or criteria, ensuring that engagements are meaningful and relevant.

Scalable Growth Strategy -

- Growth Without Manual Effort : Automation enables scalable growth strategies without the need for constant manual intervention. This is particularly beneficial for businesses or individuals managing multiple accounts.

Detailed Analytics and Insights -

- Insightful Data : Most automation tools provide detailed analytics on engagement, follower growth, and content performance. This data can be invaluable for refining strategies and understanding audience preferences.

Improved User Experience -

- Maintaining Authenticity : Despite automation, tools like Instagenie can be configured to maintain an authentic online presence. Engagements are made with real accounts, preventing the accumulation of bot followers and ensuring a genuine connection with the audience.

Cost-Effective Solution -

- Cost Savings : Compared to hiring staff or outsourcing tasks, Instagram automation tools offer a cost-effective way to manage and grow your Instagram presence. They can handle a wide range of tasks without the overhead costs associated with human labor.

Customizable Automation -

- Tailored Automation Rules : Users can customize automation rules to suit their specific needs and goals. This flexibility allows for a highly tailored approach to Instagram management, ensuring that automation works seamlessly with your unique strategy.

Compliance and Ethical Considerations -

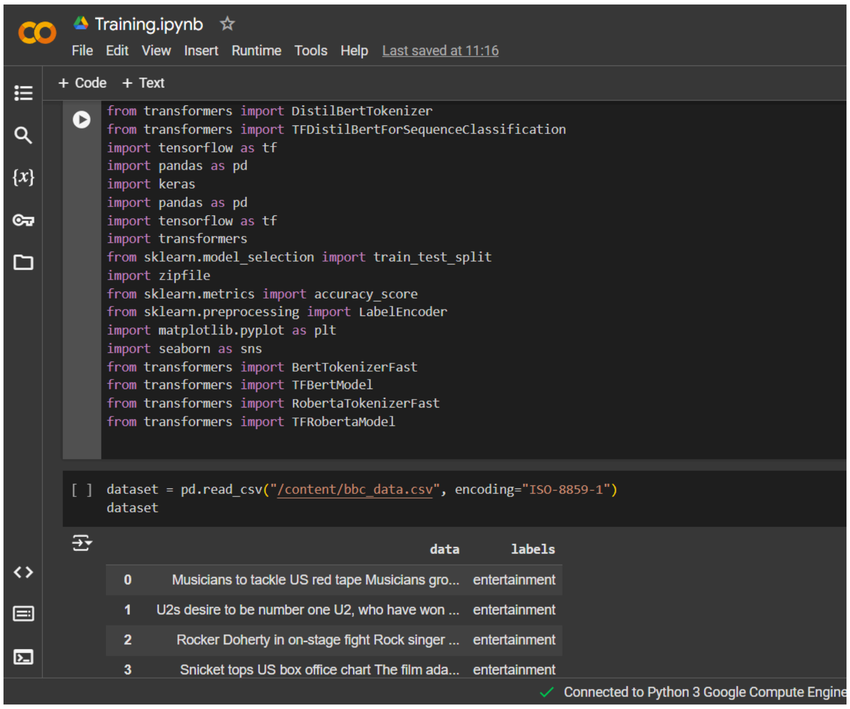
- Responsible Automation : Using automation tools responsibly and in accordance with Instagram's guidelines ensures that your account remains compliant and avoids potential penalties.

CHAPTER - 5

RESULTS AND DISCUSSIONS

5.1 ANALYSIS AND DISCUSSION OF RESULTS :

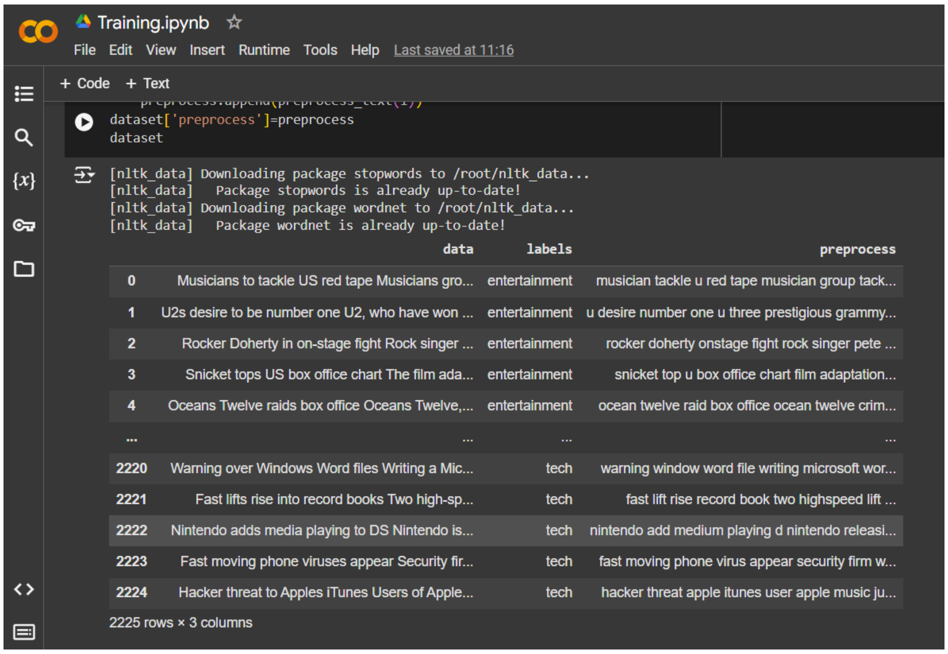
- To import various libraries from Hugging Face's `transformers`, TensorFlow, and other machine learning tools to work with pre-trained transformer models for sequence classification tasks, such as `DistilBERT`, `BERT`, and `RoBERTa`. It also includes data preprocessing, model training, and evaluation utilities like accuracy score and label encoding.



	data	labels
0	Musicians to tackle US red tape Musicians gro...	entertainment
1	U2s desire to be number one U2, who have won ...	entertainment
2	Rocker Doherty in on-stage fight Rock singer ...	entertainment
3	Snicket tops US box office chart The film ada...	entertainment

Fig. 5.1.1

- To loads a CSV file named "bbc_data.csv" into a pandas DataFrame . The dataset likely contains text data, possibly news articles from the BBC, for further analysis or modeling. and prepprossesing the dataet



	data	labels	preprocess
0	Musicians to tackle US red tape Musicians gro...	entertainment	musician tackle u red tape musician group tack...
1	U2s desire to be number one U2, who have won ...	entertainment	u desire number one u three prestigious grammy...
2	Rocker Doherty in on-stage fight Rock singer ...	entertainment	rocker doherty onstage fight rock singer pete ...
3	Snicket tops US box office chart The film ada...	entertainment	snicket top u box office chart film adaptation...
4	Oceans Twelve raids box office Oceans Twelve,...	entertainment	ocean twelve raid box office ocean twelve crim...
...	...	...	...
2220	Warning over Windows Word files Writing a Mic...	tech	warning window word file writing microsoft wor...
2221	Fast lifts rise into record books Two high-sp...	tech	fast lift rise record book two highspeed lift ...
2222	Nintendo adds media playing to DS Nintendo is...	tech	nintendo add medium playing d nintendo releasi...
2223	Fast moving phone viruses appear Security fir...	tech	fast moving phone virus appear security firm w...
2224	Hacker threat to Apples iTunes Users of Apple...	tech	hacker threat apple itunes user apple music ju...

2225 rows × 3 columns

Fig. 5.1.2

- The code serializes the `val_texts` and `val_labels` variables into binary format and saves them as `testtext.pkl` and `testlabel.pkl` files using Python's `pickle` module. This allows for efficient storage and later loading of the data.

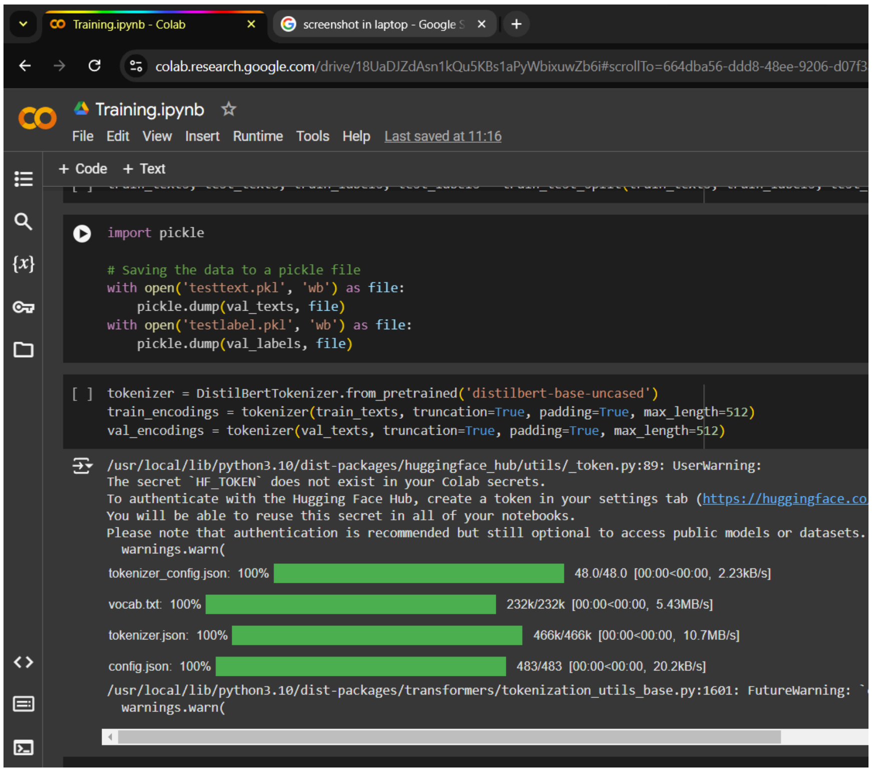


Fig. 5.1.3

- The code creates TensorFlow `Dataset` objects for training (`train_dataset`) and validation (`val_dataset`) by converting the encoded text data (`train_encodings`, `val_encodings`) and their corresponding labels (`train_labels`, `val_labels`) into tensor slices. These datasets are used for efficient batching and model training in TensorFlow.

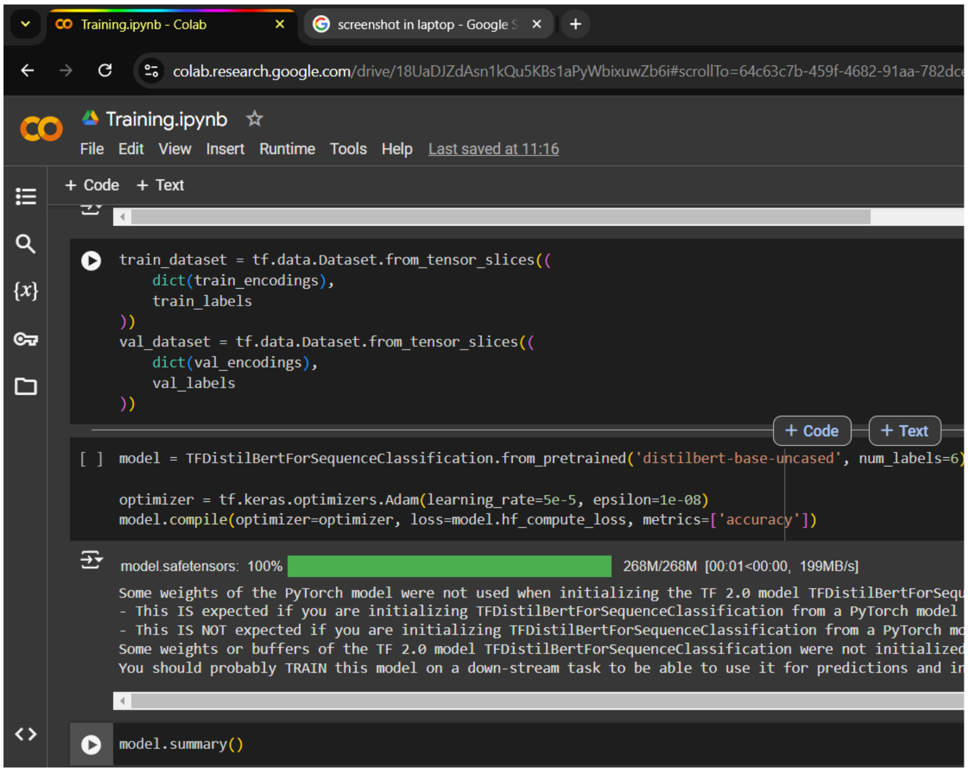


Fig. 5.1.4

5.2 FUTURE ENHANCEMENTS :

The system can be further developed and expanded to address evolving requirements and challenges in social media interaction management. Key future directions include -

1. Integration of Multilingual Support - Expanding the system's capabilities to process and analyze text in multiple languages will increase its applicability to a global audience.

2. Enhanced Emotion Detection - Incorporating more complex emotional classifications, such as anger, joy, or fear, will improve the system’s ability to generate nuanced and empathetic responses.

3. Real-Time Response Optimization - Implementing real-time learning mechanisms, such as reinforcement learning, can optimize responses dynamically based on user feedback and interaction patterns.

4. Integration with Other Social Media Platforms - Extending the system to work seamlessly across multiple social media platforms will enable centralized management of interactions.

CHAPTER - 6

CONCLUSION

In conclusion, the integration of automation tools like Instagenie into social media strategies offers a compelling approach for marketers and influencers seeking to enhance their visibility and engagement on platforms such as Instagram. By automating likes, comments, and post-scheduling, Instagenie provides users with a powerful tool to maintain consistent interaction, thereby improving algorithmic visibility and fostering growth. The AI-driven capabilities of these tools ensure that engagement remains steady, allowing users to focus on other critical aspects of their brand development without sacrificing online presence.

However, while the benefits of automation are clear, it is essential to approach these tools with caution and responsibility. Automated engagement must be carefully managed to avoid appearing spammy or inauthentic, which can damage a brand's reputation and lead to penalties from platforms like Instagram that have strict policies against certain forms of automation. The effectiveness of such tools hinges on the thoughtful selection of target audiences and the customization of comments to ensure relevance and authenticity. Moreover, automation should not replace genuine interaction but rather complement a broader social media strategy that includes real-time engagement and personalized communication. The use of tools like Instagenie should be seen as a means to enhance, not replace, the human touch that is crucial in building authentic connections with audiences.

Ultimately, Instagenie exemplifies how automation, when used responsibly, can play a pivotal role in optimizing social media management. It contributes to a more dynamic and responsive online community, leading to stronger customer relationships and greater brand loyalty. As social media continues to evolve, the thoughtful application of automation tools will be key in navigating the complex landscape of online engagement and maintaining a competitive edge.

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APPENDIX

A. SOURCE CODE

```
from flask import Flask, request, jsonify, render_template
from flask_cors import CORS
from werkzeug.utils import secure_filename
import os
import pickle
import pandas as pd
import numpy as np
from flask import session
import uuid
import json
from datetime import datetime
from dbconnect import *
from flask import Flask, send_file
import os
import datetime
import hashlib

from flask import Flask, request, jsonify, session
from transformers import DistilBertTokenizer
from transformers import TFDistilBertForSequenceClassification
import tensorflow as tf
import pandas as pd
import keras
import pandas as pd
import tensorflow as tf
import transformers
from sklearn.model_selection import train_test_split
import zipfile
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from transformers import BertTokenizerFast
from transformers import TFBertModel
from transformers import RobertaTokenizerFast
from transformers import TFRobertaModel
import os
import hashlib
import time
import json
```

```
import json
import base64
import json
import requests
from bs4 import BeautifulSoup

app = Flask(__name__)
app.config['SESSION_TYPE'] = 'memfileuploadencryptd'
app.config['SECRET_KEY'] = 'super secret key'

import os
import datetime
import hashlib

import pickle
import google.generativeai as genai

genai.configure(api_key="AIzaSyApHISlpUH-ouDy7QChKIFMzR7h23ydVaE")


generation_config = {
  "temperature": 0,
  "top_p": 0.95,
  "top_k": 64,
  "max_output_tokens": 8192,
  "response_mime_type": "text/plain",
}
safety_settings = [
  {
    "category": "HARM_CATEGORY_HARASSMENT",
    "threshold": "BLOCK_NONE",
  },
  {
    "category": "HARM_CATEGORY_HATE_SPEECH",
    "threshold": "BLOCK_MEDIUM_AND_ABOVE",
  },
  {
    "category": "HARM_CATEGORY_SEXUALLY_EXPLICIT",
    "threshold": "BLOCK_MEDIUM_AND_ABOVE",
  },
  {
    "category": "HARM_CATEGORY_DANGEROUS_CONTENT",
    "threshold": "BLOCK_MEDIUM_AND_ABOVE",
  },
]
```

```
model = genai.GenerativeModel(
  model_name="gemini-1.5-flash",
  safety_settings=safety_settings,
  generation_config=generation_config,
  system_instruction="You are an expert at teaching science to kids. Your task is to engage in conversations about science and answer questions. Explain scientific concepts so that they are easily understandable. Use analogies and examples that are relatable. Use humor and make the conversation both educational and interesting. Ask questions so that you can better understand the user and improve the educational experience. Suggest way that these concepts can be related to the real world with observations and experiments.",
)



chat_session = model.start_chat(
    history=[]
)

save_directory = "model"
loaded_tokenizer = DistilBertTokenizer.from_pretrained(save_directory)
loaded_model = TFDistilBertForSequenceClassification.from_pretrained(save_directory)
@app.route('/')
def hello():
    message= ''
    return render_template("login.html")

@app.route('/index')
def index():
    message= ''
    return render_template("login.html")

@app.route('/signup')
def signup():
    message= ''
    return render_template("sign_up.html",message = message)

@app.route('/signin')
def signin():
    message= ''
    return render_template("login.html",message = message)


@app.route('/follow')
def follow():
    message= ''
    return render_template("follow.html",message = message)
```

```
@app.route('/createpost')
def createpost():
    message= ''
    return render_template("createpost.html",message = message)

@app.route('/instagram')
def instagram():
    userid=session['id']
    dataQuery = "select * from profile where userid='"+str(userid)+"'"
    print(dataQuery)
    dataInfo = recoredselect(dataQuery)



    message= ''
    c, conn=connection()
    query ='''SELECT
        p.id,
        p.userid,
        p.image,
        p.description,
        p.dateandtime,
        p.likes,
        u.username,
        u.image
    FROM postimage p
    JOIN PROFILE u ON p.userid = u.userid'''
    df = pd.read_sql(query, conn)
    result=df.values.tolist()

    if(dataInfo):
        data=dataInfo[0][5]

        for i in result:
            text=i[3]
            test_text=text
            label_info=['Entertainment', 'Unknown', 'Business', 'Sport', 'Politics',
                'Tech']
            predict_input = loaded_tokenizer.encode(test_text,
                                    truncation=True,
                                    padding=True,
                                    return_tensors="tf")

            output = loaded_model(predict_input)[0]
```

```
 prediction_value = tf.argmax(output, axis=1).numpy()[0]
           print(text)
           print(label_info[prediction_value])
           if(data==label_info[prediction_value]):
              file_id=i[0]
              userid=session['id']
            dataQuery = "select * from postlike where userid='"+str(userid)+"' &&
postid='"+str(file_id)+"'"
              print(dataQuery)

              dataInfo = recoredselect(dataQuery)
              print(dataInfo)
              if(dataInfo):
                 continue
              sql1='insert into postlike(userid,postid) values("%s","%s")' % \
                           (userid,file_id)
              print(sql1)
              inserquery(sql1)
              dataQuery = "select * from postimage where id='"+str(file_id)+"'"
              print(dataQuery)
              dataInfo = recoredselect(dataQuery)
              print(dataInfo[0][5])
              count=dataInfo[0][5]+1
              sql1='update postimage set likes="%s" where id="%s"' % \
                           (count,file_id)
              print(sql1)
              inserquery(sql1)
              message=test_text
              response = chat_session.send_message(message)
              model_response = response.text
              post_id = i[0]
              comment_text = model_response
              userid=session['id']
              sql1 = "INSERT INTO comments (userid, postid, comment_text) VALUES (%s, %s, %s)"
              values = (userid, post_id, comment_text)

              inserqueryparam(sql1,values)


    return render_template("instagram.html",message =
message,post_data=result,comments=commentget())
```

```
@app.route('/profile')
def profile():
    message= ''
    return render_template("profile.html",message = message)
from datetime import datetime
@app.route('/postinfo', methods=["POST","GET"])
def postinfo():
    photo=request.files["photo"]
    photo_name = photo.filename
    photo.save("static/image/" + photo_name)
    name="static/image/" + photo_name
    description = request.form["description"]
    userid=session['id']
    now = datetime.now()
    formatted_time = now.strftime("%Y-%m-%d %H:%M:%S")
    sql1='insert into postimage(userid,image,description,dateandtime,likes)
values("%s","%s","%s","%s","%s")' % \
                    (userid,name,description,formatted_time,0)
    print(sql1)
    inserquery(sql1)
    return render_template('instagram.html', message ="Post Upload Sucessfully" ,
post_data=datacollect(),comments=commentget(),name=session['name'])
def datacollect():
    c, conn=connection()
    query ='''SELECT
            p.id,
            p.userid,
            p.image,
            p.description,
            p.dateandtime,
            p.likes,
            u.username,
            u.image
        FROM postimage p
        JOIN PROFILE u ON p.userid = u.userid'''
    df = pd.read_sql(query, conn)
    result=df.values.tolist()
    return result
def commentget():
    c, conn=connection()
    query ='''SELECT * FROM comments'''
    df = pd.read_sql(query, conn)
    result=df.values.tolist()
    finalresult=[]
    for i in result:
        i[2]=int(i[2])
        finalresult.append(i)
```

```
return finalresult

@app.route('/profileinfo', methods=["POST","GET"])
def profileinfo():
    photo=request.files["photo"]
    photo_name = photo.filename
    photo.save("static/profile/" + photo_name)
    name="static/profile/" + photo_name
    description = request.form["description"]
    autolike = request.form["category"]
    userid=session['id']
    username=session['name']
    now = datetime.now()
    print(autolike)
    formatted_time = now.strftime("%Y-%m-%d %H:%M:%S")
    sql1='insert into profile(userid,username,image,description,Autolike)
values("%s","%s","%s","%s","%s")' % \
                (userid,username,name,description,autolike)
    print(sql1)
    inserquery(sql1)

    return render_template('instagram.html', message ="Post Upload Sucessfully"
,post_data=datacollect(),comments=commentget(), name=session['name'])

@app.route('/register', methods=["POST","GET"])
def register():

    if request.method == 'POST':

        email = request.form["email"]
        password= request.form["password"]
        username= request.form["username"]
        name= request.form["fullname"]
        sql1='insert into account(username,email,password,name) values("%s","%s","%s","%s")' % \
                (username,email,password,name)
        print(sql1)
        inserquery(sql1)
        message=email+" account Created Sucessfully"
    return render_template('login.html', message =message)

@app.route('/authorised',methods = ["GET","POST"])
def authorised():
    message= ''
    email= request.form["email"]
    password= request.form["password"]
    print("-----------------------------")
    print(email)
```

```
 dataInfo = recoredselect(dataQuery)
    print(dataInfo)
    if(dataInfo):
        session['id'] = dataInfo[0][0]
        session['name'] = dataInfo[0][1]
        c, conn=connection()
        query ='''SELECT
            p.id,
            p.userid,
            p.image,
            p.description,
            p.dateandtime,
            p.likes,
            u.username,
            u.image
        FROM postimage p
        JOIN PROFILE u ON p.userid = u.userid'''
        df = pd.read_sql(query, conn)
        result=df.values.tolist()
        return render_template('instagram.html', message =dataInfo ,post_data=result,
name=session['name'])
    else:
        return render_template('login.html', message =message)

@app.route('/like',methods=['GET','POST'])
def like():
    file_id=request.args.get('id')
    userid=session['id']
    dataQuery = "select * from postlike where userid='"+str(userid)+"' && postid='"+file_id+"'"
    print(dataQuery)

    dataInfo = recoredselect(dataQuery)
    print(dataInfo)
    if(dataInfo):
         return render_template('instagram.html', message ="Post Upload Sucessfully"
,post_data=datacollect(),comments=commentget(), name=session['name'])
    sql1='insert into postlike(userid,postid) values("%s","%s")' % \
                (userid,file_id)
    print(sql1)
    inserquery(sql1)
    dataQuery = "select * from postimage where id='"+file_id+"'"
    print(dataQuery)
    dataInfo = recoredselect(dataQuery)
    print(dataInfo[0][5])
    count=dataInfo[0][5]+1
    sql1='update postimage set likes="%s" where id="%s"' % \
                (count,file_id)
```

```
print(sql1)
    inserquery(sql1)

    return render_template('instagram.html', message ="Post Upload Sucessfully"
,post_data=datacollect(),comments=commentget(), name=session['name'])




@app.route('/add_comment', methods=['POST'])
def add_comment():
    post_id = request.form['post_id']
    comment_text = request.form['comment_text']
    userid=session['id']
    sql1='insert into comments(userid,postid,comment_text) values("%s","%s","%s")' % \
                (userid,post_id,comment_text)
    print(sql1)
    inserquery(sql1)
    return render_template('instagram.html', message ="Post Upload Sucessfully"
,post_data=datacollect(),comments=commentget(), name=session['name'])




@app.route('/home')
def home():
    return render_template("index.html")




if __name__ == '__main__':
    app.run(debug=True)
```

B. SCREENSHOTS

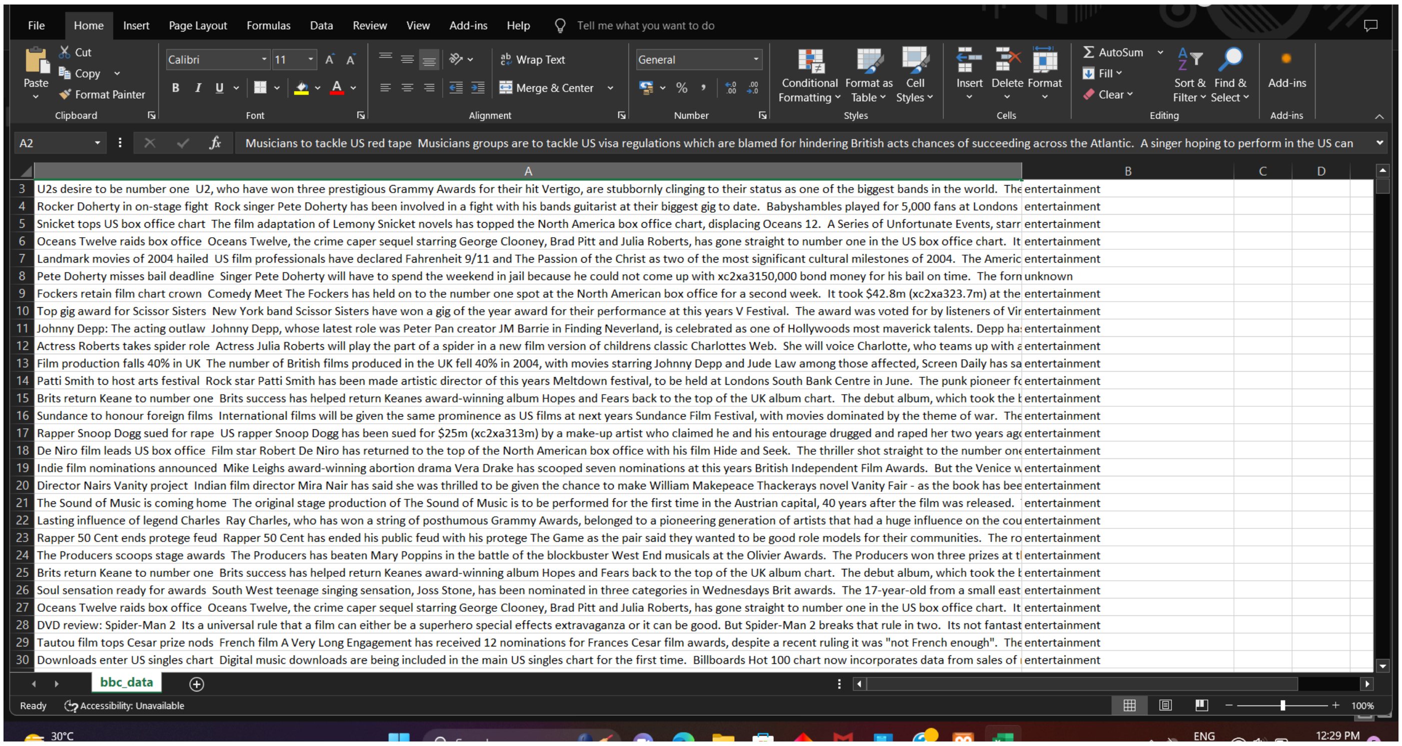

Fig. 1 Dataset

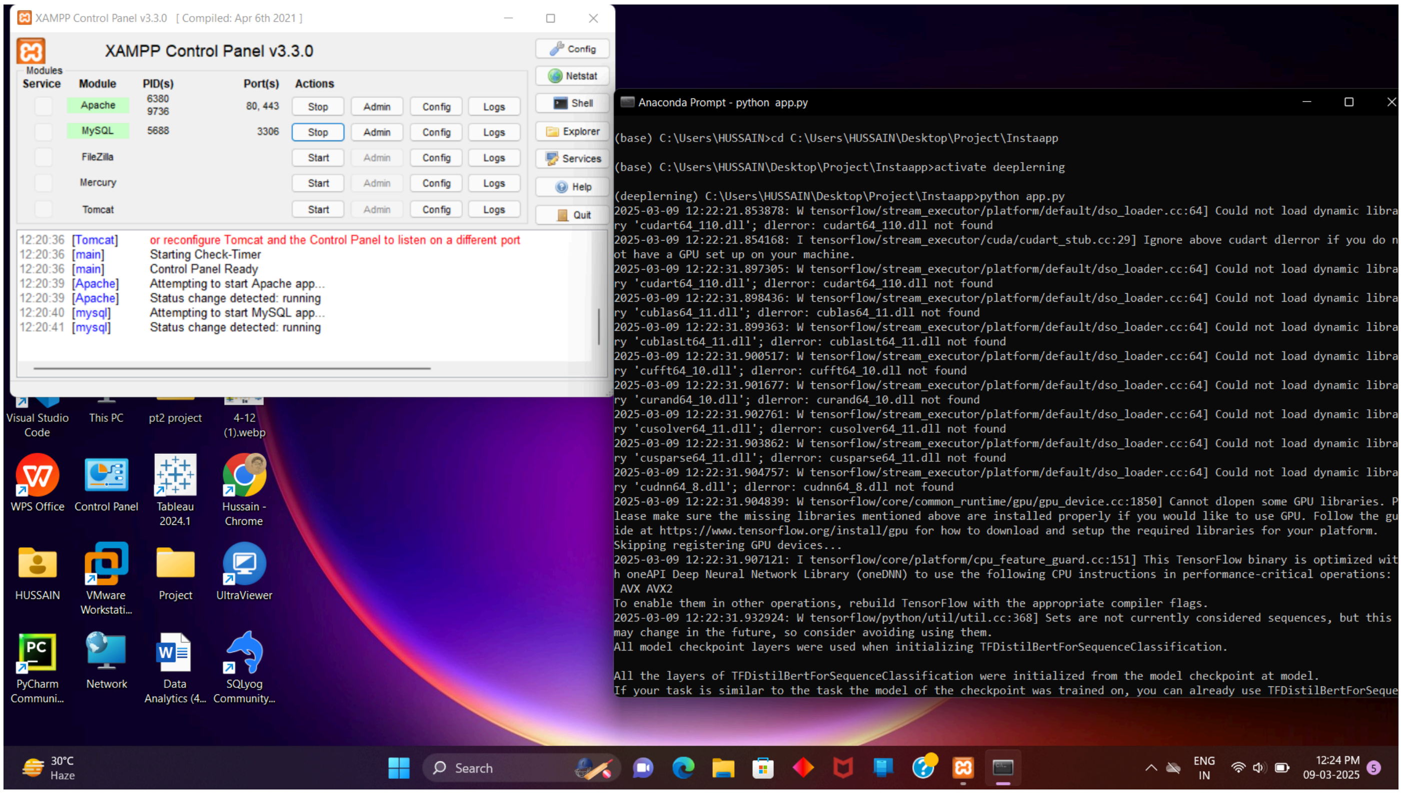

Fig. 2 Initializing the data server

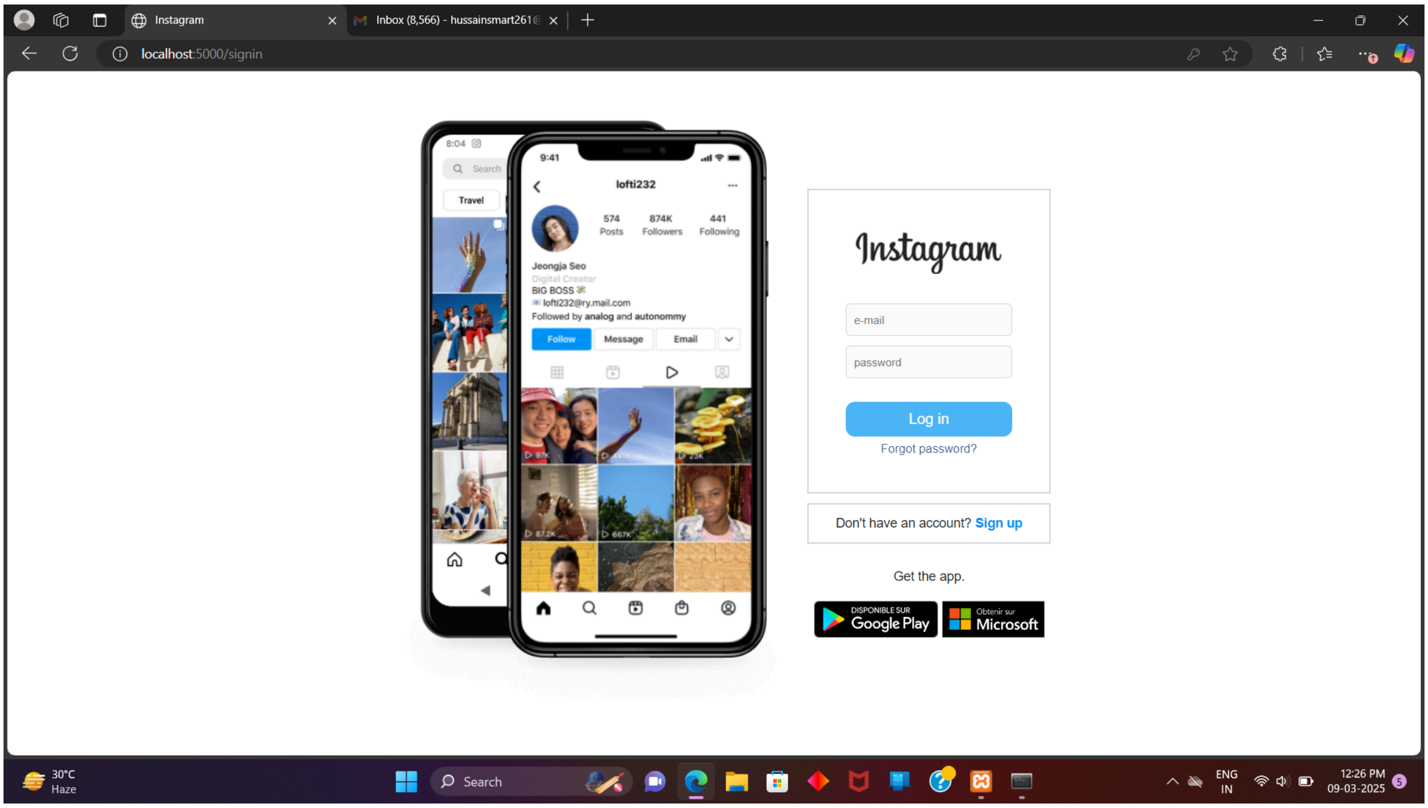

Fig. 3 Login Page

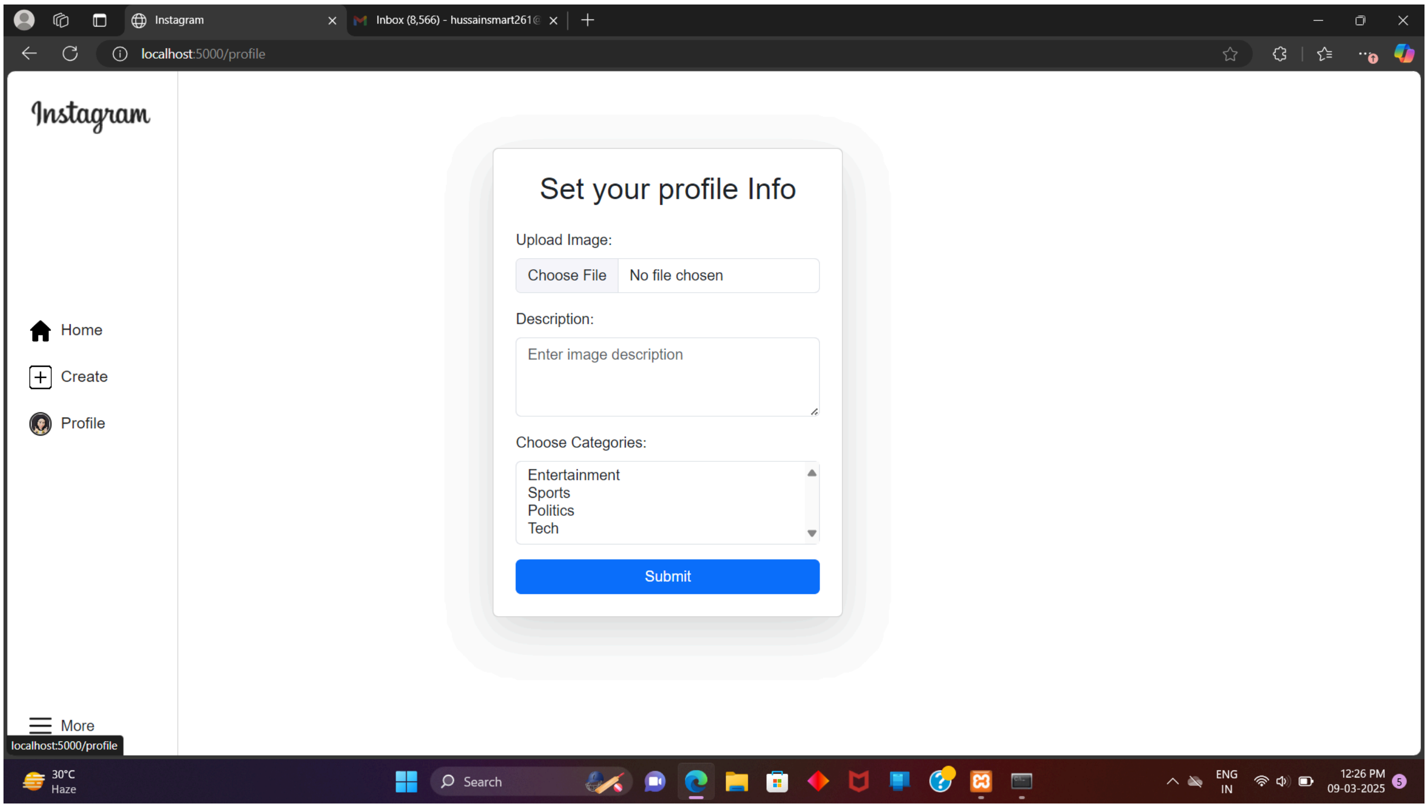

Fig. 4 Setting up the user profile

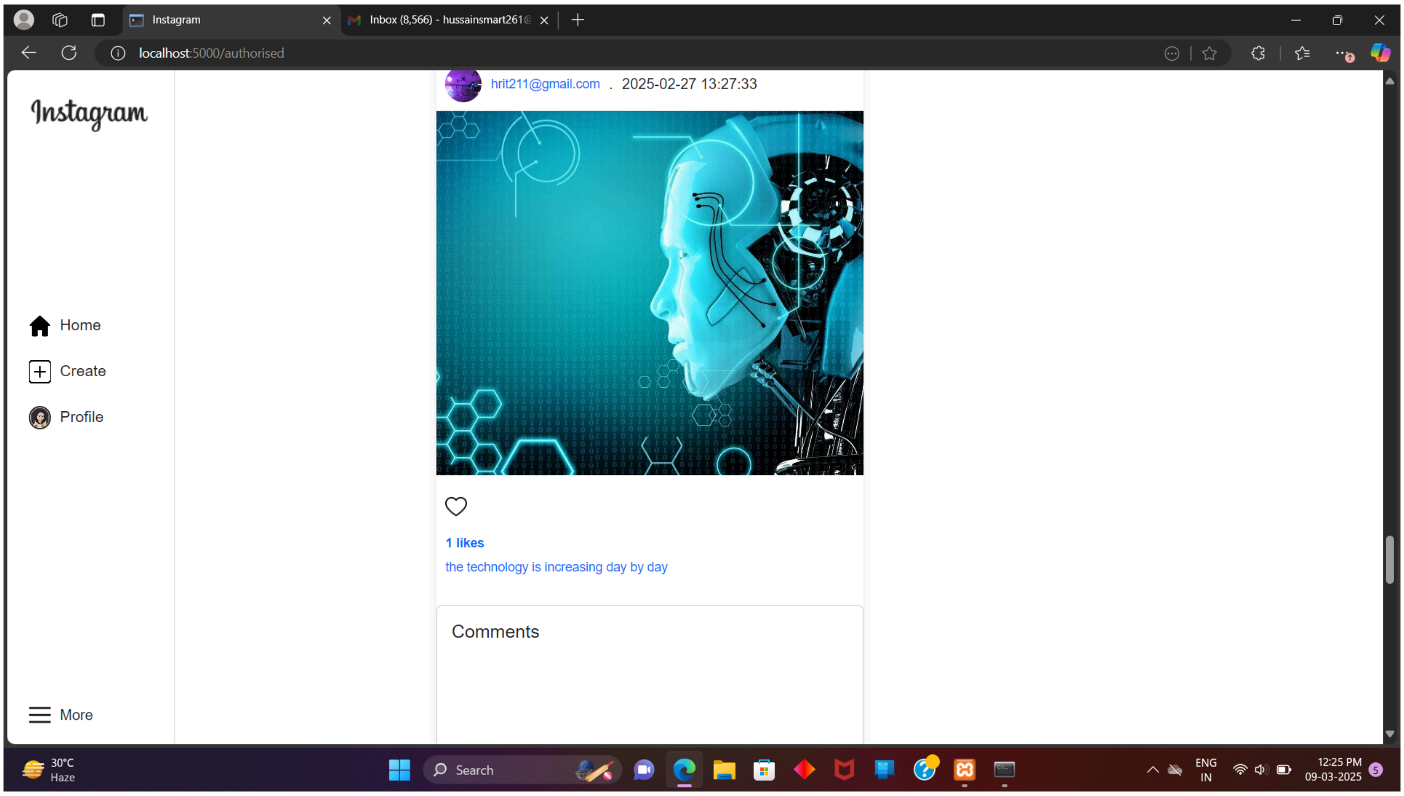

Fig. 5 Adding Automatic Posts

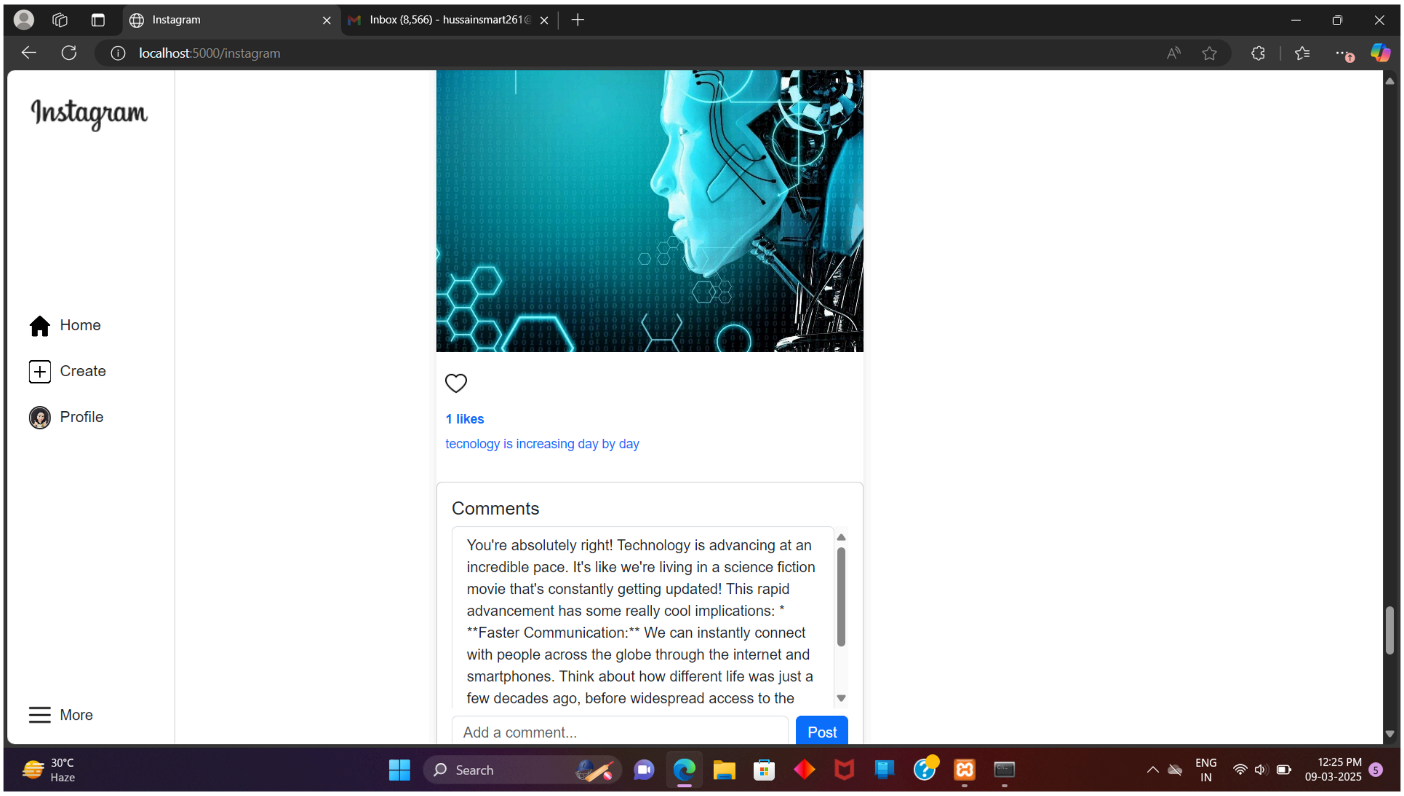

Fig. 6 Adding Automatic Comments & Likes

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AI-Powered Communication: An Automated Reply System for Social Media Platforms

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***Abstract*—Nowadays social media platforms have become pivotal for engaging audiences and fostering interactions. Managing extensive user interactions manually poses significant challenges for organizations, necessitating automated solutions. This paper introduces a machine learning-based automated reply system tailored for social media platforms to streamline communication and enhance user engagement. The proposed system integrates advanced Natural Language Processing (NLP) techniques with a pre-trained BERT (Bidirectional Encoder Representations from Transformers) models to analyze user inputs, classify message sentiment (e.g., sport, business, politics, tech, entertainment, unknown), and determine intents. Based on this analysis, the system generates context-aware replies, maintaining a personalized touch to interactions. Additionally, functionalities such as auto-liking posts and following users based on engagement levels are incorporated to recognize and appreciate user contributions, fostering a sense of community. By automating responses and interactions, the system reduces manual intervention, ensures timely communication, and offers an efficient approach to managing large-scale engagements on social media platforms. This framework not only improves user experience but also provides organizations with a scalable and effective communication solution. It achieved a detection accuracy of 90.42% BBC datasets, with F-measure scores of 87.17%.**

Keywords— Automated Reply System, Natural Language Processing, BERT, Sentiment Analysis, Social Media Engagement.

I. Introduction

The rise of internet and mobile devices has led to increased use of social media platforms like Facebook, blogs, Instagram, and Twitter for expressing feelings [1], [2]. With billions of users worldwide, social media has emerged as a vital component of international communication. For organizations, these platforms serve as essential tools for interacting with their audiences, fostering engagement, and nurturing customer relationships. Nowadays, people want to openly share their thoughts, opinions, evaluations, and feedback about products or any viral news. As a result, companies and organizations are looking to social media for insightful information [3]. Social media platforms facilitate free speech and content production by enabling end users to produce and distribute various types of material at any time and from any location. Changes and trends can be swiftly shared or broadcast as content thanks to these free capabilities, which enable the detection of trends or alterations in reality virtually in real-time [4], [5]. Social media websites have already permeated all aspects of society, serving as important information sources in a variety of fields [6]. Consequently, a number of studies that use and analyze social media content have been carried out on a regular basis. Sentiment analysis (SA), which converts unprocessed social media user input into useful information, is therefore in high demand [7].

The proliferation of social media platforms has fundamentally transformed the way individuals and organizations interact. Platforms such as Twitter, Facebook, Instagram, and LinkedIn enable users to exchange ideas, share information, and engage with diverse audiences in real time. For businesses, public figures, and organizations, these platforms present unparalleled opportunities to build relationships, foster brand loyalty, and enhance public engagement. However, managing extensive user interactions manually is increasingly challenging, particularly as audiences grow and user-generated content multiplies exponentially. These challenges highlight the pressing need for automated solutions that streamline communication while maintaining the quality and personalization expected by users.

In artificial intelligence (AI), SA is one of the most prevalent and difficult problems. [8], [9] It uses automatic tools to identify psychological information, including attitudes, thoughts, and feelings, that are expressed in text and suggested in news, blogs, and social networks. SA determines whether a sentence, document, clause, or paragraph contains polarity (positive or negative viewpoints). Due to the ability to identify consumer feelings regarding a product, it is utilized for commercial objectives [10]. In a similar vein, firms can find problems and modify their products to satisfy customer needs by examining survey results and social media discussions [11]. In real time, SA can assist in identifying significant issues. Numerous machine learning (ML) techniques have served as the foundation for earlier research on SA [12]. One important aspect of social media analysis is the ability to efficiently manage and process content. Effective methods for handling the massive volumes of content that are created and shared in real time are essential. Furthermore, because the contexts are not standardized as prevalent data, the processing methods must be carefully examined [13].

Many academics are working to develop effective techniques to address the growing challenges of big data and extend SA to a wide range of applications, from marketing plans to financial forecasts, medical exams, and other areas [14]. Furthermore, in order to demonstrate the effectiveness of various deep learning (DL) techniques, some researchers concentrate on assessing them [15]. With the use of ML or DL approaches, ML-related SA processes digital phrases and assigns a vectorized value to a word using statistical techniques such as word embedding.

Social media platforms have become indispensable for modern communication, enabling real-time interactions between organizations and their audiences. Engaging with users on social media involves responding to comments, addressing queries, acknowledging feedback, and fostering meaningful discussions. However, the traditional methods of managing these tasks manually are labor-intensive, time-consuming, and prone to inconsistencies. These challenges often lead to delayed responses, missed engagement opportunities, and inefficient use of resources, especially as user interactions increase exponentially.

This paper provides a machine-learning-based automated reply system for social media sites that uses the BERT technique to circumvent constraints. The suggested system uses cutting-edge Natural Language Processing (NLP) methods to automate social media conversation, guaranteeing prompt, pertinent, and customized exchanges. By doing this, the system improves operating efficiency, resolves frequent problems like inconsistent messaging and delayed responses, and lessens the strain of manual monitoring. This paper's major goal is to suggest and create a system that automates social media interactions without sacrificing engagement levels. The following are the study's main objectives:

Automate Social Media Interactions: To reduce the manual effort involved in handling user posts, comments, and queries by deploying an intelligent automated reply system capable of managing large-scale interactions.

Emotion Classification Using BERT: To integrate a BERT model for accurate sentiment and emotion classification, allowing the system to recognize and react to user emotions across categories such as sport, business, politics, tech, entertainment, and unknown.

Context-Aware Replies: To generate context-aware, personalized replies that improve user engagement, ensuring that responses are relevant, timely, and aligned with the user's intent.

Auto-Liking: To implement automatic actions, such as liking posts based on user engagement levels, thereby fostering a sense of community and enhancing user satisfaction.

II. RELATED WORKS

A.G. Lopez-Herrera, J.I.A. Salas, and M.M. Aguero-Torales (2021): "An overview of multilingual sentiment analysis and deep learning on social media data. This study examines 24 works that address developments in sentiment analysis from 2017 to 2020, spanning 23 languages and 11 social media platforms. It highlights the lack of deep learning models for multilingual aspect-based sentiment analysis, indicates a move toward cross-lingual and code-switching techniques, and observes stagnation in simpler designs like CNN or LSTM with embedding layers. Surprisingly, transformer-based architectures are still not well studied in this field, even though they are well suited for difficult tasks".

HEMOS is a new deep learning-based fine-grained humor detection technique for social media sentiment analysis, according to "D. Li, R. Rzepka, M. Ptaszynski, and K. Araki (2020). The HEMOS system, which uses a deep learning methodology for fine-grained sentiment classification of Chinese social media data, is presented in this study. The study emphasizes how language, humor, and pictograms affect affective processing. An attention-based BiLSTM model was trained using a Chinese emoji vocabulary containing 109 Weibo emojis and a slang lexicon with 576 common Internet slang terms. The suggested approach showed notable gains in sentiment polarity prediction on Weibo by adding new sentiment kinds, "optimistic humorous" and "pessimistic humorous," in addition to conventional sentiment categories, demonstrating its efficacy on smaller labeled data".

In 2020, "M. Alam, F. Abid, C. Guangpei, and L.V. Yunrong created a parallel dilated convolutional neural network for smart city applications that analyzes social media sentiment. This study uses sentiment analysis on social media to investigate how deep learning might improve smart city applications (SCAs). In order to generate rich textual representations from social media, it presents a domain-specific distributed word representation (DS-DWR), which efficiently handles uncommon and invisible phrases. Furthermore, to capture long-term contextual semantics while lowering computational costs, the suggested design uses a parallel dilated convolutional neural network (PD-CNN) with three parallel dilated CNN layers and a global average pooling layer. The model is particularly effective for smart city applications since it uses various dilation rates to boost parallelism and sentiment analysis performance".

Cotton, C., and I. Priyadarshini (2021): "An innovative deep neural network for sentiment analysis based on LSTM–CNN–grid search. In order to find hidden thoughts, attitudes, and emotions in user-generated information on the web—which are essential for applications like social media and brand monitoring, customer service, and market research—this study tackles the problem. It suggests a brand-new sentiment analysis approach that combines grid search for hyperparameter optimization, convolutional neural networks (CNN), and long short-term memory (LSTM). Using criteria like accuracy, precision, sensitivity, specificity, and F1 score across several datasets, the model's performance is evaluated against baseline techniques such as CNN, K-nearest neighbor, LSTM, neural networks, LSTM-CNN, and CNN-LSTM, proving its efficacy".

"Deep learning for topic-level sentiment analysis of social media data (A.R. Pathak, M. Pandey, & S. Rautaray, 2021). This research proposes a deep learning-based topic-level sentiment analysis model to tackle the problem of evaluating streaming social media data. A topic-level attention mechanism within a long short-term memory (LSTM) network is used for sentiment analysis after sentence-level topic extraction utilizing online latent semantic indexing with a regularization constraint. The model does effective sentiment analysis and provides dynamic, scalable topic modeling over streaming short text input. It also displayed great scalability, with measures like as feature vector construction time, topics recognized per second, and sentiment analysis query response time, indicating suitability for real-time applications".

"Arousal-Infused BiDirectional LSTM for Sentiment Analysis of Government Social Media Management by Y.Y. Cheng, Y.M. Chen, W.C. Yeh, and Y.C. Chang (2021). In order to improve the public perception assessment of government and organization Facebook fan sites, this study investigates sentiment analysis. To anticipate and model detailed sentiment information, the suggested method makes use of Bi-directional Long Short-Term Memory (BiLSTM) enhanced with Valence and Arousal (VA) values. The technique achieves state-of-the-art sentiment prediction performance by first calculating VA values at the word level and then incorporating them into a deep learning model.

Results from experiments demonstrate how the model may enhance sentiment analysis of social media content, helping corporations and governments better understand and interact with public opinion".

"The sentiment analysis model for service providers' feedback was developed by K. Shakhovska, N. Shakhovska, and P. Vesely in 2020. In order to increase sentiment prediction accuracy and encourage the use of the Ukrainian language in sentiment analysis tools, this study introduces a hybrid sentiment analysis model created especially for feedback in the Ukrainian language. Support vector machines, logistic regression, XGBoost, and a rule-based algorithm are all employed in this model, which focuses on user comments from Google Maps in areas including cuisine, hotels, museums, and stores". The method has a minimum accuracy of 0.88 and has a sentiment analysis and classification visualization function. In order to help service providers enhance their offers based on customer feedback, the study also identifies frequently used positive and negative phrases.

E.-S. M. El-kenawy and M. S. F. Alharbi (2021): "Optimize machine learning programming methods for social media sentiment analysis. In order to evaluate the polarity of Twitter reviews, this work presents a hybrid optimization approach called GWOPS (Grey Wolf Optimizer and Particle Swarm Optimization) for feature selection in sentiment analysis". In order to train neural network classifiers for optimal feature selection, GWOPS narrows down the feature selection search space. Comparing GWOPS to three well-known optimization algorithms, experimental findings show how good and efficient it is, underscoring its potential to improve sentiment analysis in social media by boosting classifier performance.

"In 2023, M. S. Hossain, M. F. Rahman, M. K. Uddin, and M. K. Hossain used machine learning techniques to analyze customer sentiment and predict halal restaurants. This study uses supervised machine learning models to assess customer evaluations of halal eateries in order to identify sentiment trends. The AFINN and VADER sentiment algorithms were used to filter, clean, and classify the data gathered from Yelp reviews into positive, neutral, and negative attitudes. Five machine learning classifiers were used: logistic regression, random forest, SVM, K-Neighbors classifier, and decision tree. The study discovered that the most accurate method for categorizing attitudes was logistic regression. Through a data-driven understanding of client feedback, insights may help restaurant operators uncover customer preferences and improve the quality of their services".

"Uddin, M.K., Hossain, M.K., Rahman, M.F., and Hossain, M.S. (2023): Machine learning techniques for predicting halal eateries and analyzing customer sentiment". This study examines opinions on two halal product categories—halal travel and halal cosmetics—using Twitter data collected over a ten-year span. Twitter is a useful tool for sentiment analysis because of its microblogging feature, which enables succinct user-generated content. The Twitter search function was used to retrieve the data, which was then filtered using algorithms and examined using deep learning models such as "recurrent neural networks (RNN), long short-term memory (LSTM), and convolutional neural networks (CNN)". The maximum accuracy was obtained using a CNN-LSTM stack in conjunction with the Word2vec feature extraction method. The results show how well sophisticated machine learning techniques can comprehend customer feelings, leading to improved insights for marketing strategies promoting halal products.

III. PRINCIPLE

The principle of the proposed system revolves around leveraging machine learning techniques to automate communication on social media platforms effectively. ML-based systems can analyze vast volumes of unstructured text data, extract meaningful patterns, and generate insights that drive decision-making. In this context, the proposed automated reply system integrates a pre-trained BERT model—a state-of-the-art NLP framework—to enhance the accuracy and efficiency of message classification and intent detection. The system classifies user messages into categories such as sports, business, politics, technology, entertainment, and unknown, ensuring that responses are both relevant and personalized. The core principles underlying the system are outlined as follows:

Data-Driven Decision Making: The system relies on analyzing user-generated data (posts, comments, and messages) to derive meaningful insights, classify emotions, and generate appropriate responses. By processing large volumes of data, the system ensures consistency and accuracy in social media interactions.

Contextual Awareness: The system's backbone is the BERT model, known for its bidirectional nature, which comprehends context by considering words and phrases from both preceding and succeeding text. This ensures that replies are not only accurate but also contextually appropriate, addressing the specific needs and emotions of users.

Automation and Efficiency: By automating repetitive tasks like replying to comments, acknowledging feedback, and even performing actions such as auto-liking posts, the system minimizes manual effort, reduces response delays, and ensures consistent engagement across social media platforms.

Scalability: The system is designed to handle the dynamic and large-scale nature of social media platforms. It processes user interactions in real-time, adapting to varying volumes of data and maintaining performance without compromising quality.

Emotion-Sensitive Interaction: Emotion classification is central to the system, allowing it to identify categories such as sport, business, politics, tech, entertainment, and unknown. This enables the generation of emotionally aware and personalized replies that resonate with the user.

User Engagement Optimization: Features like auto-liking posts and following users based on engagement metrics foster a sense of community and encourage positive interactions, enhancing user satisfaction and loyalty.

These principles ensure the proposed system effectively streamlines social media communication while enhancing user satisfaction and engagement. Features like auto-liking posts and following users based on engagement levels recognize and reward user contributions, fostering sustained interactions. By automating these tasks, the system allows organizations to focus on strategic priorities while maintaining a personalized and responsive digital presence.

IV. Proposed System

The proposed system is a deep learning-based automated reply framework designed to streamline communication on social media platforms. It automates the process of answering user posts, comments, and inquiries by utilizing Natural Language Processing (NLP) techniques and sophisticated deep learning models, particularly the BERT model. While keeping a high degree of personalization and relevance, the system seeks to address the major issues that businesses confront, such as inconsistent messages, delayed replies, and resource limitations.

Additionally, the proposed system includes features such as auto-liking posts and following users based on their interactions and engagement levels. These functionalities are designed to recognize and appreciate user contributions, fostering a sense of community and enhancing user satisfaction. By automating routine tasks, the system alleviates the burden on social media managers and ensures timely and efficient communication, which is vital for maintaining user engagement in a fast-paced digital environment.

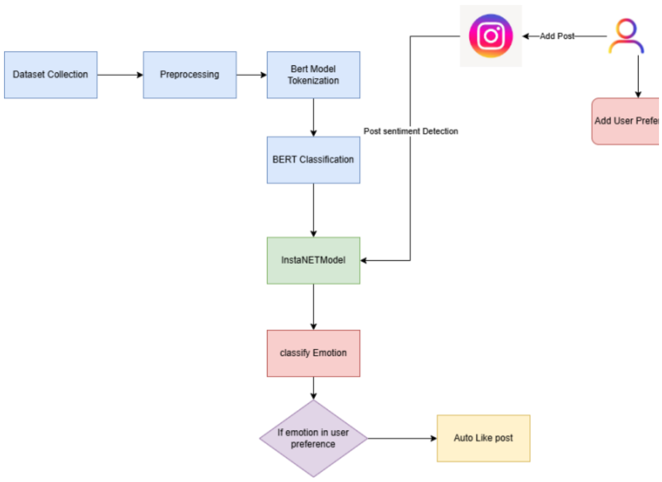

Figure 1. Deep learning-based automated reply framework

The system architecture Figure 1 integrates several essential components to streamline social media interactions. The User Input Collection module gathers content from users across platforms, which is then processed in the Text Preprocessing module to clean and format the data. The preprocessed text is analyzed using Emotion Classification with BERT, where a fine-tuned BERT model classifies emotions into categories like sport, business, politics, tech, entertainment, or unknown. Based on this classification, the Context-Aware Reply Generation module crafts personalized and relevant responses. Additionally, the Auto-Liking feature automatically engages with users by liking their posts or following them, fostering community interaction and improving user satisfaction.

1. User Input Collection

The User Input Collection Module is the starting point for the entire automated reply system. This module is responsible for interfacing with social media platforms to collect user-generated content in the form of posts, comments, or direct messages. The Instagram, allowing the system to retrieve real-time interactions from users. This module ensures that the system can process various types of inputs, including text, mentions, hashtags, or other forms of media. By providing a seamless connection to the social media platforms, this module acts as a gateway for the entire system to initiate the automated reply process.

2. Text Preprocessing

The Text Preprocessing Module cleans and gets the data ready for additional analysis when the user input is gathered. This module performs tasks including tokenization, stop word removal, stemming, and lemmatization to guarantee that the input text is in an appropriate format. By separating the input text into distinct words or subwords, tokenization facilitates system processing. Common words that don't significantly advance the text's meaning are eliminated as stop words. Lemmatization and stemming help to standardize the input text by breaking words down to their most basic forms. In order to ensure that the Emotion Classification Module can operate with clean, organized data, this preprocessing phase is crucial for eliminating noise and unnecessary data.

3. Emotion Classification Using BERT

The core of the system is the Emotion Classification Module, which uses the BERT (Bidirectional Encoder Representations from Transformers) model to determine the purpose and emotion of user input. This module makes use of the bidirectional architecture of BERT to comprehend context from a sentence's preceding and succeeding words. BERT categorizes the input into predetermined groups, including sports, business, politics, technology, entertainment, or unknown. It is fine-tuned on a labeled dataset of social media interactions. This module guarantees that the system comprehends the user's intent and emotional tone by correctly identifying the emotion and topic. This serves as the basis for producing a pertinent answer.

4. Context-Aware Reply Generation

After classifying the user input into a specific category, the Context-Aware Reply Generation Module creates a response that aligns with the user’s sentiment and topic. The module uses predefined templates or a rule-based system to generate replies tailored to the classified emotion. For instance, positive comments on sports may trigger congratulatory or appreciative replies, while business-related queries may elicit informative or formal responses. This module ensures that responses are not only contextually appropriate but also personalized based on the tone of the input. It helps maintain a natural flow in conversations, enhancing user engagement by addressing their concerns or feedback promptly.

5. Auto-Liking

The Auto-Liking and Following Module is designed to improve user engagement and foster a sense of community by automating certain interactions based on user behavior. This module tracks the level of user engagement with the organization's posts, such as likes, comments, and shares. If a user is highly engaged with the content, the system will automatically like their posts.

This automatic interaction not only increases the sense of recognition but also encourages users to participate more actively in discussions, leading to a stronger community and improved overall satisfaction.

V. Results and Discussion

To evaluate the performance, we used the Kaggle BBC dataset, which consists of 2,225 entries, to assess our emotion classification system. The system utilizes a pretrained BERT model for emotion analysis and categorization, targeting six distinct categories: entertainment, unknown, business, sport, politics, and tech. To evaluate the model's efficacy, evaluation measures such as "accuracy, precision, recall, and F1 score" were calculated.

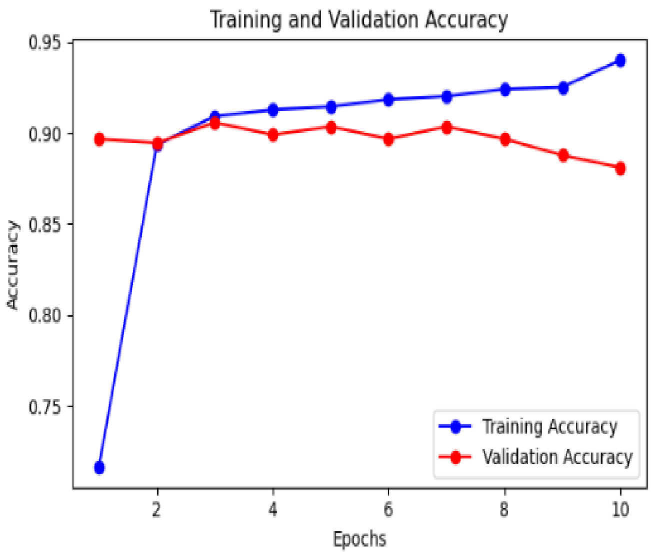

Figure 2. Training and validation Accuracy

The figure2 shows the training and validation accuracy over the course of training. As seen in the graph, the model shows steady improvement in both training and validation accuracy, with a slight gap between the two indicating some overfitting. However, the validation accuracy remains close to the training accuracy, suggesting good generalization to unseen data.

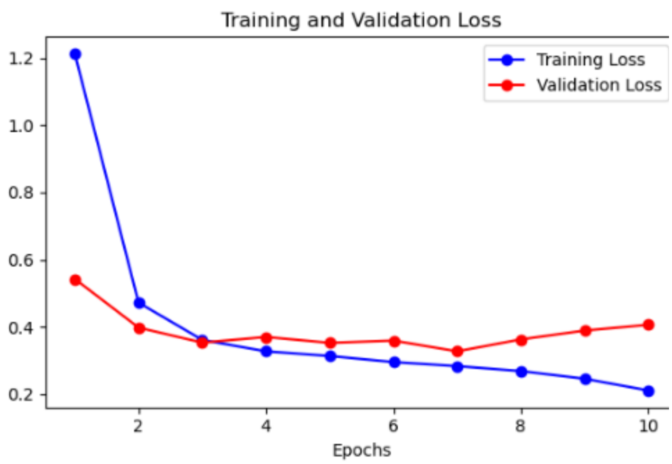

Figure 3. Training and validation loss

The figure3 shows the training and validation loss over the course of training. This loss graph indicates that both training and validation losses decrease steadily, with the training loss consistently lower than the validation loss. This suggests that the model is learning effectively but could benefit from additional regularization techniques to minimize overfitting further.

The Confusion Matrix provides additional insight into where the model is making mistakes.

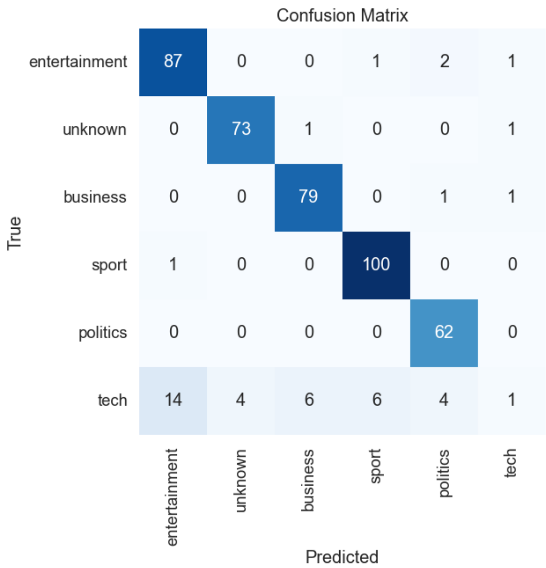

Figure 4. Confusion Matrix

From the confusion matrix, Sport and Politics were the easiest categories for the model to classify with no misclassifications between them. Entertainment had a few misclassifications into other categories (e.g., some entertainment posts were misclassified as tech or sport), but overall, the classification was solid. Tech had some confusion with the Business and Entertainment categories, which is understandable since there is overlap in the language used in discussions about technology and business, or tech-related entertainment.

Accuracy	Precision	Recall	F1-Score
90.34	85.84	90.34	87.26

The table shows that the proposed model is performing exceptionally well in terms of identifying the correct category from a set of possible emotions. With an accuracy of 90.34%, the system can accurately classify most of the user-generated content into the appropriate categories. This high accuracy indicates that the system is reliable for real-world in managing and responding to social media posts across various topics.

VI. Conclusion

In conclusion, the rapid growth of social media platforms has made it increasingly challenging for organizations to manage large-scale user interactions efficiently. Manual responses to user posts, comments, and queries are not only labor-intensive but also prone to inconsistencies and delays, which can negatively impact user experience. The machine learning-based automatic response system presented in this research uses the potent BERT model and sophisticated Natural Language Processing (NLP) approaches to overcome these difficulties. The proposed system automates social media interactions, classifying user inputs based on emotions and intent across various categories such as sport, business, politics, tech, entertainment, and unknown. By incorporating sentiment analysis and context-aware reply generation, the system ensures personalized, timely, and relevant responses, enhancing user engagement. Additionally, the integration of auto-liking actions based on user engagement further contributes to fostering a sense of community and improving user satisfaction The system offers a scalable solution that reduces manual workload, streamlines communication, and ensures that responses are consistently aligned with user expectations. It represents a significant advancement in automating social media management while maintaining high-quality user interactions.

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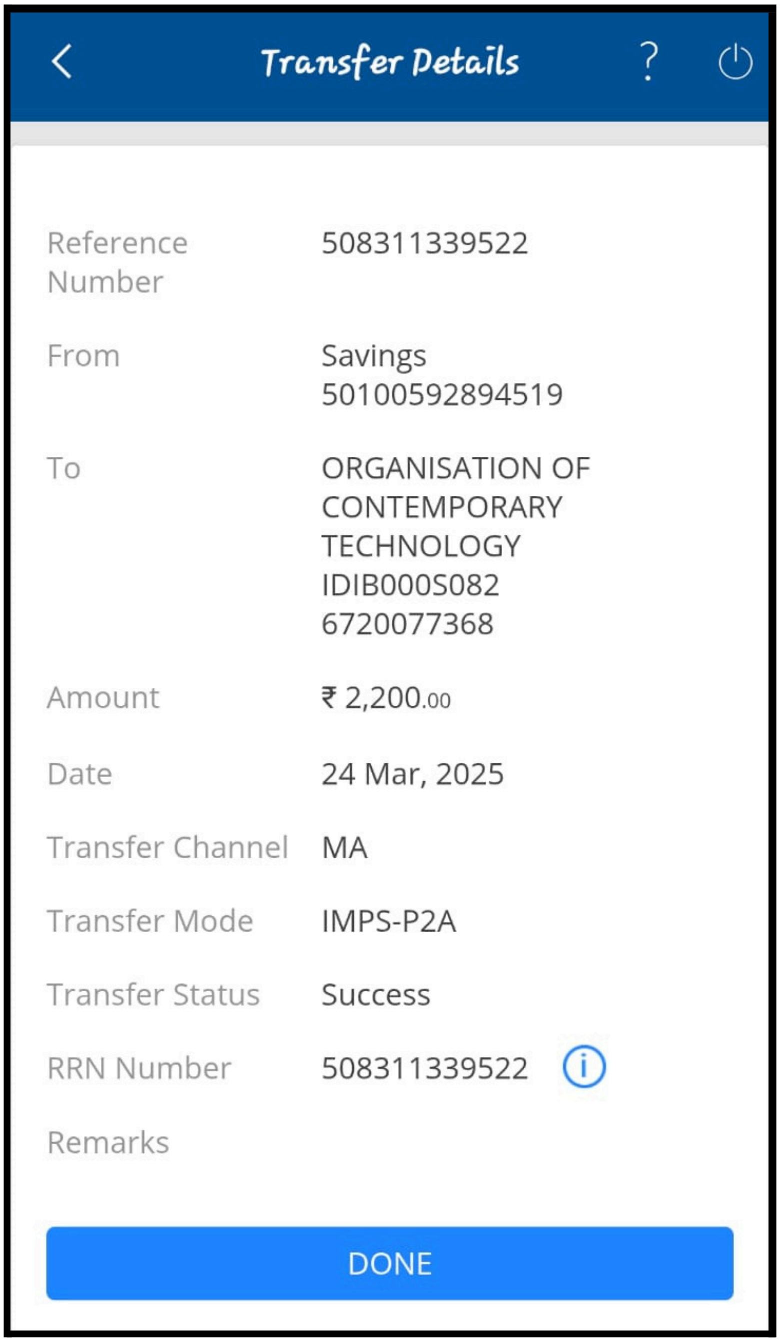

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AI-Powered Communication: An Automated Reply System for Social Media Platforms

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***Abstract*—Nowadays social media platforms have become pivotal for engaging audiences and fostering interactions. Managing extensive user interactions manually poses significant challenges for organizations, necessitating automated solutions. This paper introduces a machine learning-based automated reply system tailored for social media platforms to streamline communication and enhance user engagement. The proposed system integrates advanced Natural Language Processing (NLP) techniques with a pre-trained BERT (Bidirectional Encoder Representations from Transformers) models to analyze user inputs, classify message sentiment (e.g., sport, business, politics, tech, entertainment, unknown), and determine intents. Based on this analysis, the system generates context-aware replies, maintaining a personalized touch to interactions. Additionally, functionalities such as auto-liking posts and following users based on engagement levels are incorporated to recognize and appreciate user contributions, fostering a sense of community. By automating responses and interactions, the system reduces manual intervention, ensures timely communication, and offers an efficient approach to managing large-scale engagements on social media platforms. This framework not only improves user experience but also provides organizations with a scalable and effective communication solution. It achieved a detection accuracy of 90.42% BBC datasets, with F-measure scores of 87.17%.**

Keywords*— *Automated Reply System, Natural Language Processing, BERT, Sentiment Analysis, Social Media Engagement.

I. INTRODUCTION

The rise of internet and mobile devices has led to increased use of social media platforms like Facebook, blogs, Instagram, and Twitter for expressing feelings [1], [2]. With billions of users worldwide, social media has emerged as a vital component of international communication. For organizations, these platforms serve as essential tools for interacting with their audiences, fostering engagement, and nurturing customer relationships. Nowadays, people want to openly share their thoughts, opinions, evaluations, and feedback about products or any viral news. As a result, companies and organizations are looking to social media for insightful information [3]. Social media platforms facilitate free speech and content production by enabling end users to produce and distribute various types of material at any time and from any location. Changes and trends can be swiftly shared or broadcast as content thanks to these free capabilities, which enable the detection of trends or alterations in reality virtually in real-time [4], [5]. Social media websites have already permeated all aspects of society, serving as important information sources in a variety of fields [6]. Consequently, a number of studies that use and analyze social media content have been carried out on a regular basis. Sentiment analysis (SA), which converts unprocessed social media user input into useful information, is therefore in high demand [7].

The proliferation of social media platforms has fundamentally transformed the way individuals and organizations interact. Platforms such as Twitter, Facebook, Instagram, and LinkedIn enable users to exchange ideas, share information, and engage with diverse audiences in real time. For businesses, public figures, and organizations, these platforms present unparalleled opportunities to build relationships, foster brand loyalty, and enhance public engagement. However, managing extensive user interactions manually is increasingly challenging, particularly as audiences grow and user-generated content multiplies exponentially. These challenges highlight the pressing need for automated solutions that streamline communication while maintaining the quality and personalization expected by users.

In artificial intelligence (AI), SA is one of the most prevalent and difficult problems. [8], [9] It uses automatic tools to identify psychological information, including attitudes, thoughts, and feelings, that are expressed in text and suggested in news, blogs, and social networks. SA determines whether a sentence, document, clause, or paragraph contains polarity (positive or negative viewpoints). Due to the ability to identify consumer feelings regarding a product, it is utilized for commercial objectives [10]. In a similar vein, firms can find problems and modify their products to satisfy customer needs by examining survey results and social media discussions [11]. In real time, SA can assist in identifying significant issues. Numerous machine learning (ML) techniques have served as the foundation for earlier research on SA [12]. One important aspect of social media analysis is the ability to efficiently manage and process content. Effective methods for handling the massive volumes of content that are created and shared in real time are essential. Furthermore, because the contexts are not standardized as prevalent data, the processing methods must be carefully examined [13].

Many academics are working to develop effective techniques to address the growing challenges of big data and extend SA to a wide range of applications, from marketing plans to financial forecasts, medical exams, and other areas [14]. Furthermore, in order to demonstrate the effectiveness of various deep learning (DL) techniques, some researchers concentrate on assessing them [15]. With the use of ML or DL approaches, ML-related SA processes digital phrases and assigns a vectorized value to a word using statistical techniques such as word embedding.

Social media platforms have become indispensable for modern communication, enabling real-time interactions between organizations and their audiences. Engaging with users on social media involves responding to comments, addressing queries, acknowledging feedback, and fostering meaningful discussions. However, the traditional methods of managing these tasks manually are labor-intensive, time-consuming, and prone to inconsistencies. These challenges often lead to delayed responses, missed engagement opportunities, and inefficient use of resources, especially as user interactions increase exponentially.

This paper provides a machine-learning-based automated reply system for social media sites that uses the BERT technique to circumvent constraints. The suggested system uses cutting-edge Natural Language Processing (NLP) methods to automate social media conversation, guaranteeing prompt, pertinent, and customized exchanges. By doing this, the system improves operating efficiency, resolves frequent problems like inconsistent messaging and delayed responses, and lessens the strain of manual monitoring. This paper's major goal is to suggest and create a system that automates social media interactions without sacrificing engagement levels. The following are the study's main objectives:

Automate Social Media Interactions: To reduce the manual effort involved in handling user posts, comments, and queries by deploying an intelligent automated reply system capable of managing large-scale interactions.

Emotion Classification Using BERT: To integrate a BERT model for accurate sentiment and emotion classification, allowing the system to recognize and react to user emotions across categories such as sport, business, politics, tech, entertainment, and unknown.

Context-Aware Replies: To generate context-aware, personalized replies that improve user engagement, ensuring that responses are relevant, timely, and aligned with the user's intent.

Auto-Liking: To implement automatic actions, such as liking posts based on user engagement levels, thereby fostering a sense of community and enhancing user satisfaction.

II. Related Works

A.G. Lopez-Herrera, J.I.A. Salas, and M.M. Aguero-Torales (2021): "An overview of multilingual sentiment analysis and deep learning on social media data. This study examines 24 works that address developments in sentiment analysis from 2017 to 2020, spanning 23 languages and 11 social media platforms. It highlights the lack of deep learning models for multilingual aspect-based sentiment analysis, indicates a move toward cross-lingual and code-switching techniques, and observes stagnation in simpler designs like CNN or LSTM with embedding layers. Surprisingly, transformer-based architectures are still not well studied in this field, even though they are well suited for difficult tasks".

13 HEMOS is a new deep learning-based fine-grained humor detection technique for social media sentiment analysis, according to "D. Li, R. Rzepka, M. Ptaszynski, and K. Araki (2020). The HEMOS system, which uses a deep learning methodology for fine-grained sentiment classification of Chinese social media data, is presented in this study. The study emphasizes how language, humor, and pictograms affect affective processing. An attention-based BiLSTM model was trained using a Chinese emoji vocabulary containing 109 Weibo emojis and a slang lexicon with 576 common Internet slang terms. The suggested approach showed notable gains in sentiment polarity prediction on Weibo by adding new sentiment kinds, "optimistic humorous" and "pessimistic humorous," in addition to conventional sentiment categories, demonstrating its efficacy on smaller labeled data".

In 2020, "M. Alam, F. Abid, C. Guangpei, and L.V. Yunrong created a parallel dilated convolutional neural network for smart city applications that analyzes social media sentiment. This study uses sentiment analysis on social media to investigate how deep learning might improve smart city applications (SCAs). In order to generate rich textual representations from social media, it presents a domain-specific distributed word representation (DS-DWR), which efficiently handles uncommon and invisible phrases. Furthermore, to capture long-term contextual semantics while lowering computational costs, the suggested design uses a parallel dilated convolutional neural network (PD-CNN) with three parallel dilated CNN layers and a global average pooling layer. The model is particularly effective for smart city applications since it uses various dilation rates to boost parallelism and sentiment analysis performance".

Cotton, C., and I. Priyadarshini (2021): "An innovative deep neural network for sentiment analysis based on LSTM–CNN–grid search. In order to find hidden thoughts, attitudes, and emotions in user-generated information on the web—which are essential for applications like social media and brand monitoring, customer service, and market research—this study tackles the problem. It suggests a brand-new sentiment analysis approach that combines grid search for hyperparameter optimization, convolutional neural networks (CNN), and long short-term memory (LSTM). Using criteria like accuracy, precision, sensitivity, specificity, and F1 score across several datasets, the model's performance is evaluated against baseline techniques such as CNN, K-nearest neighbor, LSTM, neural networks, LSTM-CNN, and CNN-LSTM, proving its efficacy".

"Deep learning for topic-level sentiment analysis of social media data (A.R. Pathak, M. Pandey, & S. Rautaray, 2021). This research proposes a deep learning-based topic-level sentiment analysis model to tackle the problem of evaluating streaming social media data. A topic-level attention mechanism within a long short-term memory (LSTM) network is used for sentiment analysis after sentence-level topic extraction utilizing online latent semantic indexing with a regularization constraint. The model does effective sentiment analysis and provides dynamic, scalable topic modeling over streaming short text input. It also displayed great scalability, with measures like as feature vector construction time, topics recognized per second, and sentiment analysis query response time, indicating suitability for real-time applications".

"Arousal-Infused BiDirectional LSTM for Sentiment Analysis of Government Social Media Management by Y.Y. Cheng, Y.M. Chen, W.C. Yeh, and Y.C. Chang (2021). In order to improve the public perception assessment of government and organization Facebook fan sites, this study investigates sentiment analysis. To anticipate and model detailed sentiment information, the suggested method makes use of Bi-directional Long Short-Term Memory (BiLSTM) enhanced with Valence and Arousal (VA) values. The technique achieves state-of-the-art sentiment prediction performance by first calculating VA values at the word level and then incorporating them into a deep learning model.

Results from experiments demonstrate how the model may enhance sentiment analysis of social media content, helping corporations and governments better understand and interact with public opinion".

"The sentiment analysis model for service providers' feedback was developed by K. Shakhovska, N. Shakhovska, and P. Vesely in 2020. In order to increase sentiment prediction accuracy and encourage the use of the Ukrainian language in sentiment analysis tools, this study introduces a hybrid sentiment analysis model created especially for feedback in the Ukrainian language. Support vector
25 machines, logistic regression, XGBoost, and a rule-based
5 algorithm are all employed in this model, which focuses on user comments from Google Maps in areas including cuisine, hotels, museums, and stores". The method has a minimum accuracy of 0.88 and has a sentiment analysis and classification visualization function. In order to help service providers enhance their offers based on customer feedback, the study also identifies frequently used positive and negative phrases.

E.-S. M. El-kenawy and M. S. F. Alharbi (2021): "Optimize machine learning programming methods for social media sentiment analysis. In order to evaluate the polarity of Twitter reviews, this work presents a hybrid optimization approach called GWOPS (Grey Wolf Optimizer and Particle Swarm Optimization) for feature selection in sentiment analysis". In order to train neural network classifiers for optimal feature selection, GWOPS narrows down the feature selection search space. Comparing GWOPS to three well-known optimization algorithms, experimental findings show how good and efficient it is, underscoring its potential to improve sentiment analysis in social media by boosting classifier performance.

"In 2023, M. S. Hossain, M. F. Rahman, M. K. Uddin, and M. K. Hossain used machine learning techniques to analyze customer sentiment and predict halal restaurants. This study uses supervised machine learning models to assess customer evaluations of halal eateries in order to identify sentiment trends. The AFINN and VADER sentiment algorithms were used to filter, clean, and classify the data gathered from Yelp reviews into positive, neutral, and negative attitudes. Five machine learning classifiers were used: logistic regression, random forest, SVM, K-Neighbors classifier, and decision tree. The study discovered that the most accurate method for categorizing attitudes was logistic regression. Through a data-driven understanding of client feedback, insights may help restaurant operators uncover customer preferences and improve the quality of their services".

"Uddin, M.K., Hossain, M.K., Rahman, M.F., and Hossain, M.S. (2023): Machine learning techniques for predicting halal eateries and analyzing customer sentiment". This study examines opinions on two halal product categories—halal travel and halal cosmetics—using Twitter data collected over a ten-year span. Twitter is a useful tool for sentiment analysis because of its microblogging feature, which enables succinct user-generated content. The Twitter search function was used to retrieve the data, which was then filtered using
28 algorithms and examined using deep learning models such as "recurrent neural networks (RNN), long short-term memory (LSTM), and convolutional neural networks (CNN)". The maximum accuracy was obtained using a CNN-LSTM stack in conjunction with the Word2vec feature extraction method. The results show how well sophisticated machine learning techniques can comprehend customer feelings, leading to improved insights for marketing strategies promoting halal products.

III. PRINCIPLE

The principle of the proposed system revolves around leveraging machine learning techniques to automate communication on social media platforms effectively. ML-based systems can analyze vast volumes of unstructured text data, extract meaningful patterns, and generate insights that drive decision-making. In this context, the proposed automated reply system integrates a pre-trained BERT model—a state-of-the-art NLP framework—to enhance the accuracy and efficiency of message classification and intent detection. The system classifies user messages into categories such as sports, business, politics, technology, entertainment, and unknown, ensuring that responses are both relevant and personalized. The core principles underlying the system are outlined as follows:

Data-Driven Decision Making: The system relies on analyzing user-generated data (posts, comments, and messages) to derive meaningful insights, classify emotions, and generate appropriate responses. By processing large volumes of data, the system ensures consistency and accuracy in social media interactions.

Contextual Awareness: The system's backbone is the BERT model, known for its bidirectional nature, which comprehends context by considering words and phrases from both preceding and succeeding text. This ensures that replies are not only accurate but also contextually appropriate, addressing the specific needs and emotions of users.

Automation and Efficiency: By automating repetitive tasks like replying to comments, acknowledging feedback, and even performing actions such as auto-liking posts, the system minimizes manual effort, reduces response delays, and ensures consistent engagement across social media platforms.

Scalability: The system is designed to handle the dynamic and large-scale nature of social media platforms. It processes user interactions in real-time, adapting to varying volumes of data and maintaining performance without compromising quality.

Emotion-Sensitive Interaction: Emotion classification is central to the system, allowing it to identify categories such as sport, business, politics, tech, entertainment, and unknown. This enables the generation of emotionally aware and personalized replies that resonate with the user.

User Engagement Optimization: Features like auto-liking posts and following users based on engagement metrics foster a sense of community and encourage positive interactions, enhancing user satisfaction and loyalty.

These principles ensure the proposed system effectively streamlines social media communication while enhancing user satisfaction and engagement. Features like auto-liking posts and following users based on engagement levels recognize and reward user contributions, fostering sustained interactions. By automating these tasks, the system allows organizations to focus on strategic priorities while maintaining a personalized and responsive digital presence.

IV. Proposed System

The proposed system is a deep learning-based automated reply framework designed to streamline communication on social media platforms. It automates the process of answering user posts, comments, and inquiries by utilizing Natural Language Processing (NLP) techniques and sophisticated deep learning models, particularly the BERT model. While keeping a high degree of personalization and relevance, the system seeks to address the major issues that businesses confront, such as inconsistent messages, delayed replies, and resource limitations.

Additionally, the proposed system includes features such as auto-liking posts and following users based on their interactions and engagement levels. These functionalities are designed to recognize and appreciate user contributions, fostering a sense of community and enhancing user satisfaction. By automating routine tasks, the system alleviates the burden on social media managers and ensures timely and efficient communication, which is vital for maintaining user engagement in a fast-paced digital environment.

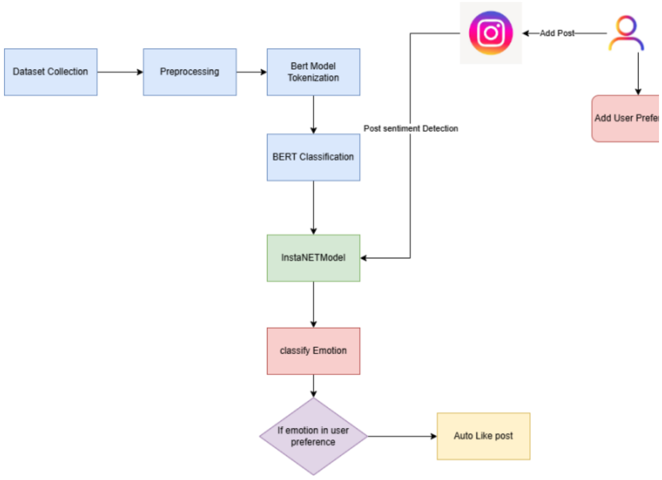

Figure 1. Deep learning-based automated reply framework

The system architecture Figure 1 integrates several essential components to streamline social media interactions. The User Input Collection module gathers content from users across platforms, which is then processed in the Text Preprocessing module to clean and format the data. The preprocessed text is analyzed using Emotion Classification with BERT, where a fine-tuned BERT model classifies emotions into categories like sport, business, politics, tech, entertainment, or unknown. Based on this classification, the Context-Aware Reply Generation module crafts personalized and relevant responses. Additionally, the Auto-Liking feature automatically engages with users by liking their posts or following them, fostering community interaction and improving user satisfaction.

1. User Input Collection

The User Input Collection Module is the starting point for the entire automated reply system. This module is responsible for interfacing with social media platforms to collect user-generated content in the form of posts, comments, or direct messages. The Instagram, allowing the system to retrieve real-time interactions from users. This module ensures that the system can process various types of inputs, including text, mentions, hashtags, or other forms of media. By providing a seamless connection to the social media platforms, this module acts as a gateway for the entire system to initiate the automated reply process.

2. Text Preprocessing

The Text Preprocessing Module cleans and gets the data ready for additional analysis when the user input is gathered. This module performs tasks including tokenization, stop word removal, stemming, and lemmatization to guarantee that the input text is in an appropriate format. By separating the input text into distinct words or subwords, tokenization facilitates system processing. Common words that don't significantly advance the text's meaning are eliminated as stop words. Lemmatization and stemming help to standardize the input text by breaking words down to their most basic forms. In order to ensure that the Emotion Classification Module can operate with clean, organized data, this preprocessing phase is crucial for eliminating noise and unnecessary data.

3. Emotion Classification Using BERT

The core of the system is the Emotion Classification Module, which uses the BERT (Bidirectional Encoder Representations from Transformers) model to determine the purpose and emotion of user input. This module makes use of the bidirectional architecture of BERT to comprehend context from a sentence's preceding and succeeding words. BERT categorizes the input into predetermined groups, including sports, business, politics, technology, entertainment, or unknown. It is fine-tuned on a labeled dataset of social media interactions. This module guarantees that the system comprehends the user's intent and emotional tone by correctly identifying the emotion and topic. This serves as the basis for producing a pertinent answer.

4. Context-Aware Reply Generation

After classifying the user input into a specific category, the Context-Aware Reply Generation Module creates a response that aligns with the user's sentiment and topic. The module uses predefined templates or a rule-based system to generate replies tailored to the classified emotion. For instance, positive comments on sports may trigger congratulatory or appreciative replies, while business-related queries may elicit informative or formal responses. This module ensures that responses are not only contextually appropriate but also personalized based on the tone of the input. It helps maintain a natural flow in conversations, enhancing user engagement by addressing their concerns or feedback promptly.

5. Auto-Liking

The Auto-Liking and Following Module is designed to improve user engagement and foster a sense of community by automating certain interactions based on user behavior. This module tracks the level of user engagement with the organization's posts, such as likes, comments, and shares. If a user is highly engaged with the content, the system will automatically like their posts.

This automatic interaction not only increases the sense of recognition but also encourages users to participate more actively in discussions, leading to a stronger community and improved overall satisfaction.

V. Results and Discussion

To evaluate the performance, we used the Kaggle BBC dataset, which consists of 2,225 entries, to assess our emotion classification system. The system utilizes a pretrained BERT model for emotion analysis and categorization, targeting six distinct categories: entertainment, unknown, business, sport, politics, and tech. To evaluate the model's efficacy, evaluation measures such as "accuracy, precision, recall, and F1 score" were calculated.

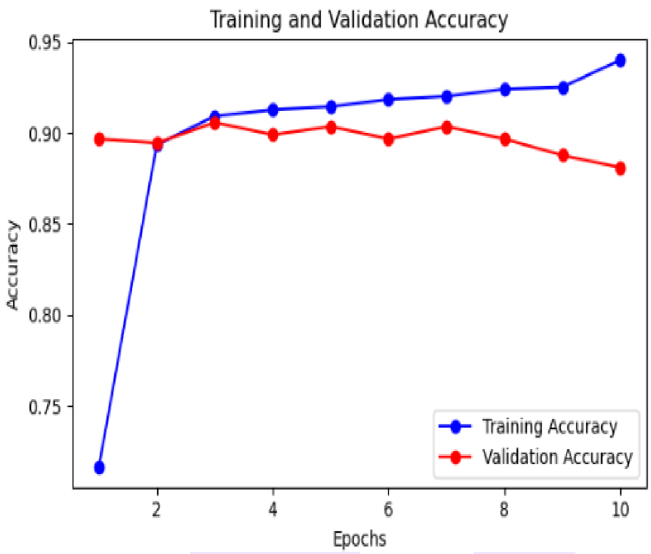

Figure 2. Training and validation Accuracy

The figure2 shows the training and validation accuracy over the course of training. As seen in the graph, the model shows steady improvement in both training and validation accuracy, with a slight gap between the two indicating some overfitting. However, the validation accuracy remains close to the training accuracy, suggesting good generalization to unseen data.

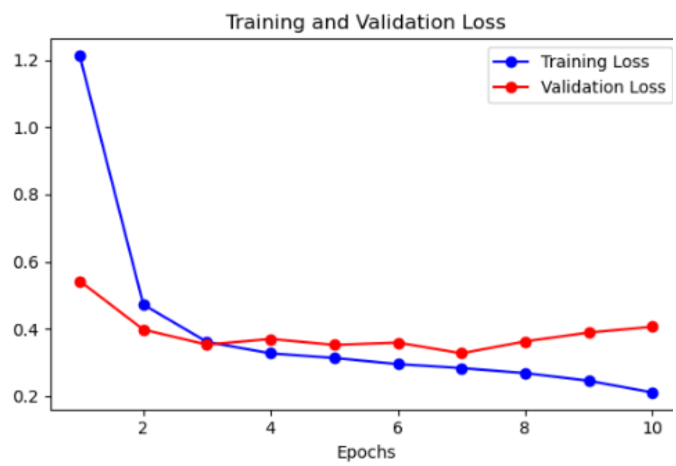

Figure 3. Training and validation loss

The figure3 shows the training and validation loss over the course of training. This loss graph indicates that both training and validation losses decrease steadily, with the training loss consistently lower than the validation loss. This suggests that the model is learning effectively but could benefit from additional regularization techniques to minimize overfitting further.

The Confusion Matrix provides additional insight into where the model is making mistakes.

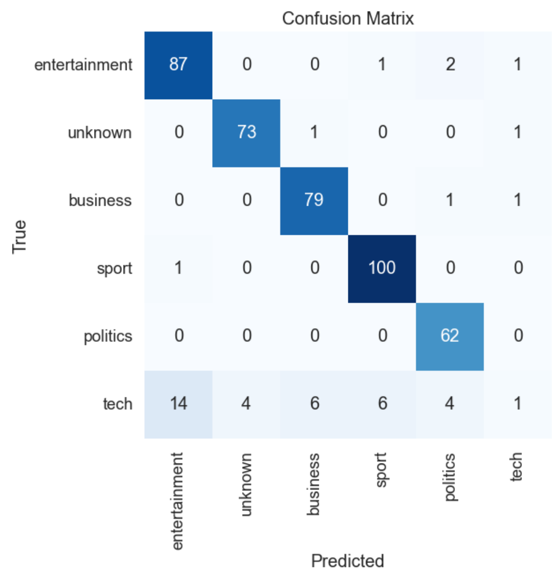

Figure 4. Confusion Matrix

From the confusion matrix, Sport and Politics were the easiest categories for the model to classify with no misclassifications between them. Entertainment had a few misclassifications into other categories (e.g., some entertainment posts were misclassified as tech or sport), but overall, the classification was solid. Tech had some confusion with the Business and Entertainment categories, which is understandable since there is overlap in the language used in discussions about technology and business, or tech-related entertainment.

Accuracy	Precision	Recall	F1-Score
90.34	85.84	90.34	87.26

The table shows that the proposed model is performing exceptionally well in terms of identifying the correct category from a set of possible emotions. With an accuracy of 90.34%, the system can accurately classify most of the user-generated content into the appropriate categories. This high accuracy indicates that the system is reliable for real-world in managing and responding to social media posts across various topics.

VI. Conclusion

In conclusion, the rapid growth of social media platforms has made it increasingly challenging for organizations to manage large-scale user interactions efficiently. Manual responses to user posts, comments, and queries are not only labor-intensive but also prone to inconsistencies and delays, which can negatively impact user experience. The machine learning-based automatic response system presented in this research uses the potent BERT model and sophisticated Natural Language Processing (NLP) approaches to overcome these difficulties. The proposed system automates social media interactions, classifying user inputs based on emotions and intent across various categories such as sport, business, politics, tech, entertainment, and unknown. By incorporating sentiment analysis and context-aware reply generation, the system ensures personalized, timely, and relevant responses, enhancing user engagement. Additionally, the integration of auto-liking actions based on user engagement further contributes to fostering a sense of community and improving user satisfaction The system offers a scalable solution that reduces manual workload, streamlines communication, and ensures that responses are consistently aligned with user expectations. It represents a significant advancement in automating social media management while maintaining high-quality user interactions.

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