DETECTING STRESS BASED ON SOCIAL INTERACTIONS IN SOCIAL NETWORKS

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ABSTRACT

With the increasing use of **social networks**, users share extensive personal content that reflects their **emotional and psychological states**. This study focuses on detecting **stress levels** by analyzing **social interactions** on platforms such as Twitter, Facebook, and Instagram. The proposed system leverages **machine learning and natural language processing (NLP)** techniques to examine textual posts, comments, and engagement patterns, identifying **stress-related cues** through sentiment analysis, linguistic markers, and behavioral features. **Graph-based analysis** of user interactions and **network centrality measures** are incorporated to assess the influence of social connections on stress levels. By detecting stress in real time, this approach can support **mental health monitoring, early intervention, and personalized recommendations**. The research demonstrates that analyzing social interactions on digital platforms provides a **scalable and effective method** for understanding user stress patterns.

Keywords: Stress Detection, Social Networks, Social Interaction Analysis, Machine Learning, NLP, Sentiment Analysis, Behavioral Features, Mental Health Monitoring, Real-Time Detection, Graph Analysis.

INTRODUCTION

With the rapid growth of **social networking platforms**, individuals increasingly share personal experiences, opinions, and daily activities online. These interactions often reflect their **emotional and psychological states**, including **stress, anxiety, and mood fluctuations**. Detecting stress through social networks has become an important research area in **mental health monitoring**, as early identification can enable timely interventions and support mental well-being.

Traditional stress assessment methods rely on **self-reported surveys or clinical interviews**, which can be time-consuming, subjective, and intrusive. In contrast, analyzing **digital social interactions** provides a non-invasive and continuous way to monitor stress patterns. Techniques such as **natural language processing (NLP), sentiment analysis, and behavioral analytics** allow researchers to extract meaningful signals from text posts, comments, and engagement patterns.

Additionally, understanding **social connections and network dynamics** can reveal how peer interactions influence individual stress levels. By combining **machine learning models, graph-based analysis, and real-time data processing**, it is possible to develop systems that detect stress accurately and efficiently. The primary goal of this study is to create a **scalable, automated framework** for detecting stress through social interactions, supporting **early intervention and mental health management**.

LITERATURE REVIEW

Recent research highlights the potential of **social networks** as a valuable source for monitoring **mental health and stress levels**. Early studies primarily relied on **self-reported surveys** or **questionnaires**, which were limited in scalability and frequency of data collection. With the proliferation of digital platforms, researchers began leveraging **user-generated content** such as posts, comments, and likes to detect emotional states.

Natural Language Processing (NLP) techniques have been widely used to analyze textual data, employing methods such as **sentiment analysis, lexical feature extraction, and linguistic inquiry** to identify stress-related expressions. Machine learning algorithms, including **support vector machines (SVM), random forests, and deep learning models**, have been applied to classify users' emotional states based on these features.

Recent studies also emphasize the role of **social network analysis**, incorporating **graph-based metrics** like centrality, clustering coefficients, and interaction patterns to understand how social ties influence stress. Multimodal approaches have further integrated **behavioral features, temporal activity patterns, and multimedia content** to improve detection accuracy.

The literature indicates that combining **textual analysis, social interaction metrics, and machine learning models** provides a robust framework for detecting stress. However, challenges remain in handling **noisy, imbalanced, and heterogeneous social data**, underscoring the need for more advanced, automated, and scalable solutions.

EXISTING SYSTEM

In existing systems, stress detection primarily relies on **traditional assessment methods** such as **self-reported surveys, psychological questionnaires, and clinical interviews**. While these methods provide direct insights into an individual's mental state, they are often **time-consuming, intrusive, and limited in scalability**, making continuous monitoring difficult.

Some current approaches use **social media analysis** with **keyword-based sentiment detection** or **basic machine learning classifiers** to identify stress-related posts. However, these systems face challenges such as **high data noise, irrelevant content, and lack of contextual understanding**. Many models focus solely on textual analysis and ignore **social interaction patterns** or **behavioral features**, which can provide critical cues about stress.

Additionally, existing systems often struggle with **real-time detection** and are unable to process the **large volume and variety of social media data**, limiting their effectiveness in proactive mental health monitoring. These limitations highlight the need for more **advanced, multimodal, and automated approaches** that integrate **textual, behavioral, and network-based analysis** for accurate stress detection.

PROPOSED SYSTEM

The proposed system aims to provide an **automated and scalable framework** for detecting stress by analyzing **social interactions** on platforms like Twitter, Facebook, and Instagram. Unlike existing systems that rely solely on text or keyword-based analysis, this approach integrates **natural language processing (NLP), sentiment analysis, and behavioral feature extraction** to capture both emotional and psychological indicators from user posts, comments, and engagement patterns.

In addition, the system employs **graph-based social network analysis** to evaluate the influence of social connections on stress levels, considering metrics such as **interaction frequency, network centrality, and community dynamics**. **Machine learning and deep learning models**, including **SVMs, random forests, CNNs, and RNNs**, are trained to classify users' stress levels based on combined textual, behavioral, and network features.

The proposed system also supports **real-time monitoring and alert generation**, enabling timely interventions for individuals exhibiting high stress. By combining **multimodal analysis, contextual understanding, and predictive modeling**, the framework improves **accuracy, efficiency, and scalability** in stress detection, providing valuable support for **mental health monitoring and personalized intervention strategies**.

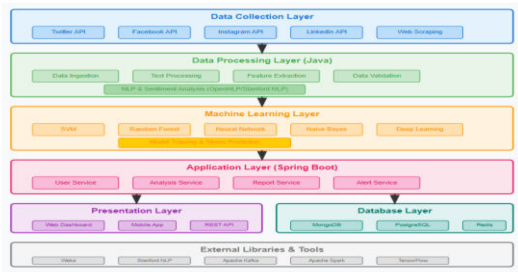
METHODOLOGY

The methodology for detecting stress based on **social interactions in social networks** involves collecting user-generated content, including posts, comments, likes, and metadata, from platforms such as Twitter, Facebook, and Instagram using APIs or web scraping. The collected data is preprocessed to remove noise, duplicates, and irrelevant content, with text normalized through **tokenization, stemming, and stop-word removal**, while behavioral and interaction data is structured for analysis. Key features are then extracted from multiple dimensions: **textual features** such as sentiment scores, stress-related keywords, and linguistic markers; **behavioral features** including posting frequency and engagement patterns; and **network features** derived from graph-based analysis, capturing social interactions, centrality, and community influence. These features are fed into **machine learning models** (e.g., SVM, Random Forest) and **deep learning models** (e.g., CNN, RNN, LSTM) to classify users into different stress levels. The system also supports **real-time monitoring and alert generation**, enabling timely intervention for users exhibiting high stress. Model performance is evaluated using metrics such as **accuracy, precision, recall, F1-score, and ROC-AUC** to ensure robustness. By combining textual, behavioral, and network analysis, this methodology provides a **scalable, accurate, and automated framework** for stress detection, supporting **mental health monitoring and early intervention strategies**.

System Model

SYSTEM ARCHITECTURE

Java Technology



Results and Discussions

PassWord.Java (Sender Side)

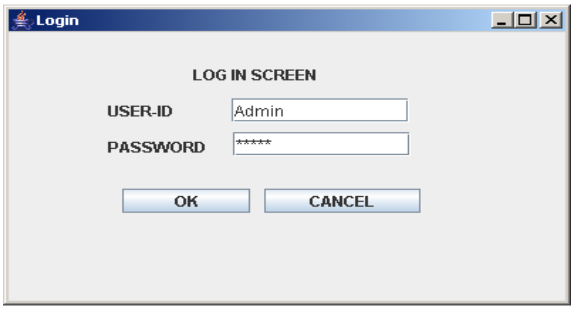
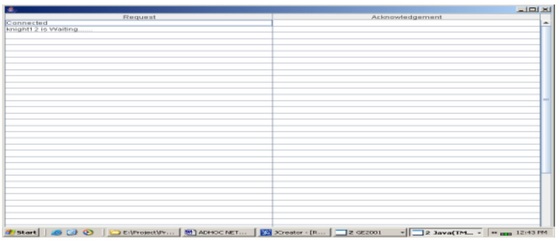
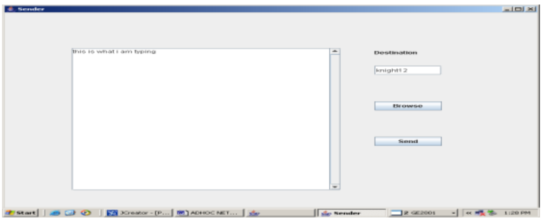


Fig:Starting The Sender

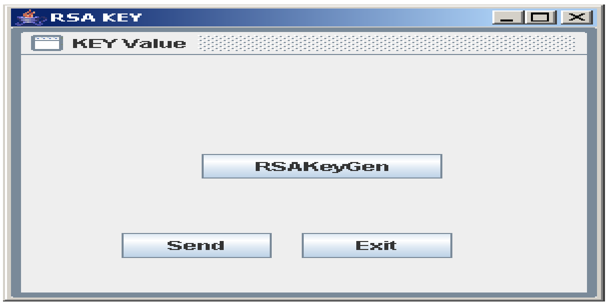


Starting the Receiver to Listen Particular Port

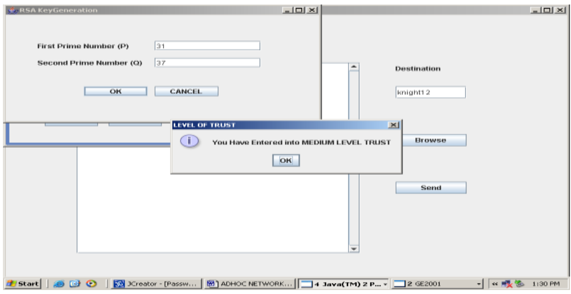
Sender Data Entry Form for (Text / File)



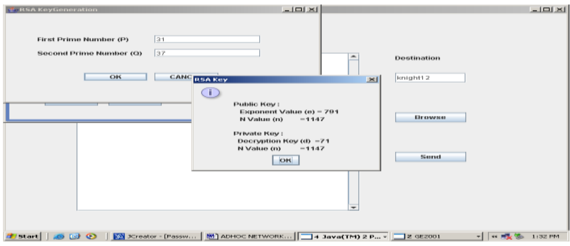
RSA KEY Generation Form



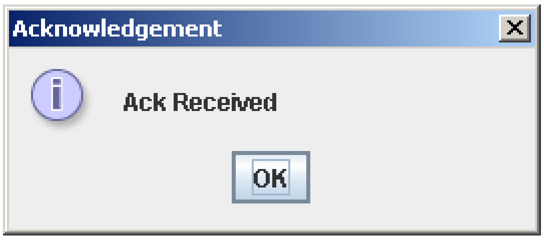
Trust Level Display



KEY Generation Display

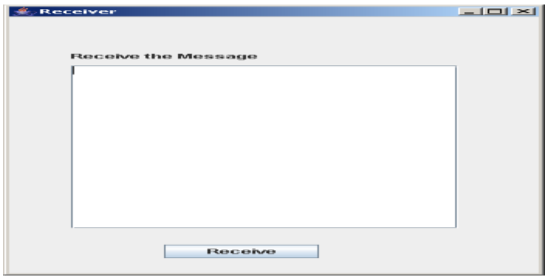


As soon as the file received the destination it gives the information like this

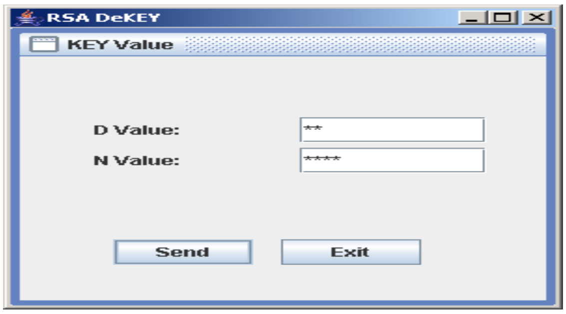


It is Mentioning that it has received Socket with Some content

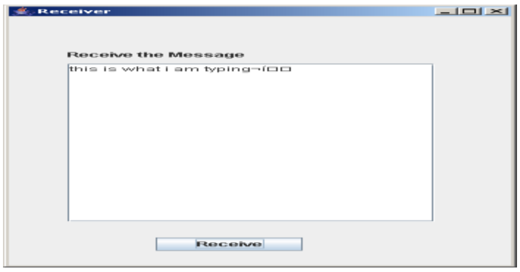
if we are pressing the receive button in below it will be shown the message after getting key.



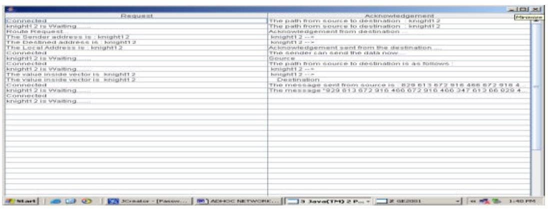
The value of D and N Value has been entered by user



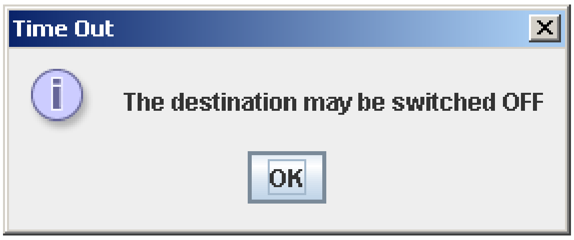
Finally Entered Information will be shown Here



Each and Every Transaction Will be Entered In this Table



If the Server has not been started then it indicates at sender



CONCLUSION

The proposed system demonstrates that analyzing **social interactions on digital platforms** can provide a reliable and scalable method for detecting stress. By integrating **natural language processing (NLP), sentiment analysis, behavioral feature extraction, and graph-based social network analysis**, the framework captures both emotional cues and the influence of social connections, offering a comprehensive understanding of users' stress levels. The use of **machine learning and deep learning models** ensures accurate classification, while **real-time monitoring and alert generation** enable timely interventions to support mental health.

Compared to traditional survey-based or keyword-only approaches, this multimodal and automated system significantly improves **detection accuracy, efficiency, and scalability**. It highlights the potential of **social media analytics** as a valuable tool for **early stress detection, mental health monitoring, and personalized intervention strategies**. By converting vast amounts of unstructured social media data into actionable insights, the system contributes to **proactive mental health management** and strengthens efforts toward **preventive care and well-being support** in digital environments.

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