COMPLAINT AND SEVERITY IDENTIFICATION FROM ONLINE FINANCIAL CONTENT

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Abstract- The automatic detection of financial complaints can benefit businesses and online merchants. Compared to manually tagged complaints, they can use this information to monitor and address issues and effectively route them to appropriate teams. This can also promote greater transparency and accountability when dealing with consumer financial products and services, strengthening the firm's brand value. In linguistic studies, complaints have been classified into severity categories based on the level of risk the complainant is prepared to accept. Furthermore, since emotions influence every speech act, an individual's emotional state considerably impacts the complaint expression. In this paper, we introduce a Financial Complaints resource, a collection of annotated complaints arising between financial institutions and consumers expressed in English on Twitter. The dataset has been enriched with the associated emotion, sentiment, and complaint severity classes. The dataset comprises 3149 complaint and 3133 non-complaint instances spanning over ten domains (e.g., credit cards, mortgages, etc.). For a comprehensive evaluation of our dataset, we develop a multi-task framework for complaint detection and severity classification with emotion recognition and sentiment classification as the additional tasks and compare it with several existing baselines.

KEYWORDS:- emotional state, emotion recognition, sentiment classification

I. INTRODUCTION

ARTIFICIAL INTELLIGENCE (AI) is transforming how people and organizations access and manage their finances. While the shift from traditional financial services to digital finance was already underway pre pandemic ,the pandemic accelerated the process as stay at- home requests became the new normal for financial institutions, and customers decided to seek more self-service options. AI and machine learning in finance cover everything from fraud detection to chat bot assistants and task automation. Other than these mainstream applications, addressing digital service complaints could be a significant commercial application for AI in finance. Compared to manually tagged complaints, automated detection of financial complaints pertaining to fraudulent transactions, delayed fund transfers, lousy customer service, etc., could help direct them to appropriate teams. This can further help promote fairness and transparency while dealing with loans, credit cards, and other consumer financial products and services, thus improving customer experience and increasing the organization's brand value. In linguistics, complaining is defined as an individual's statement of dissatisfaction with an enterprise, commodity, or event [1]. Complaints have been grouped into various degrees of severity based on the emotional intensity of the complaint, the amount of face-threat that the complainer is willing to undertake, and the complaint's motive [2], [3]. The objective of complaining could be to voice dissatisfaction, seek explanations, or both. Identifying complaints and associated severity levels in natural language is crucial for downstream application developers such as customer service chat bots [4] and commercial organizations to improve their customer support capabilities by identifying and resolving complaints [5]. Various social media and micro blogging services, such as Twitter2, Facebook3, and Tumblr4, have skyrocketed in popularity in recent years. The reason being all these forums enable effective communication amongst Web users worldwide. These social media sites, which offer millions of messages and information to be exchanged daily, are multifaceted and invaluable resources for investigating and understanding people's perceptions and evaluating the data generated by participants. Among various social media platforms, Twitter is among the most widely used social media services, with engaging individuals, famous events, and intriguing issues. The social aspect of Twitter, combined with its huge volume, has transformed it into a cost-effective data repository for exploring and evaluating activities, conduct, and user opinions. As a result, the crux of this study is analyzing Twitter-based complaints essentially focused on the Financial domain.

ii RELATED WORK

Conducting a literature survey for complaint and severity identification from online financial content requires exploring research papers, articles, and relevant sources in the fields of natural language processing (NLP), sentiment analysis, machine learning, and finance. Here's a structured approach you can follow:

1. Define Search Keywords:

- Complaint identification

- Severity detection

- Online financial content analysis

- Natural Language Processing (NLP)

- Sentiment analysis

- Machine learning in finance

2. Search Databases:

- Google Scholar

- IEEE Xplore

- ACM Digital Library

- ScienceDirect

- JSTOR

- ArXiv

- ResearchGate

3. Select Relevant Papers:

- Look for papers published in reputable journals and conferences related to NLP, sentiment analysis, machine learning, and finance.

- Pay attention to the publication date and relevance to your research objectives.

4. Read Abstracts and Introductions:

- Skim through abstracts and introductions to identify papers that focus on complaint and severity identification in financial content.

5. Review Methodologies:

- Pay attention to the methodologies employed for complaint and severity identification.

- Look for NLP techniques, sentiment analysis models, and machine learning algorithms utilized in these studies.

6. Note Key Findings:

- Summarize the key findings related to complaint and severity identification from online financial content.

- Note any significant insights, challenges, or limitations discussed in the papers.

7. Identify Trends and Gaps:

- Identify emerging trends in complaint and severity identification research.

- Highlight any gaps or areas for further exploration in the literature.

8. Organize and Analyze:

- Organize the selected papers based on themes, methodologies, findings, and relevance.

- Analyze the literature to gain a comprehensive understanding of the state-of-the-art approaches and challenges in complaint and severity identification from online financial content.

9. Synthesize and Summarize:

- Synthesize the information gathered from the literature survey.

- Summarize the existing approaches, techniques, and findings related to complaint and severity identification in online financial content.

10. Draw Conclusions and Recommendations:

- Draw conclusions based on the literature review.

- Provide recommendations for future research directions and potential improvements in complaint and severity identification methodologies.

Sample Search Queries:

- "Complaint detection in financial forums"
- "Sentiment analysis in financial texts"
- "Machine learning for severity detection in financial complaints"
- "NLP techniques for analyzing online financial content"
- "Customer feedback analysis in finance"
- "Fraud detection in financial texts"

By following these steps, you can conduct a comprehensive literature survey on complaint and severity identification from online financial content, which will serve as a valuable foundation for your research.

III METHODOLOGY

1. Complaint Submission Interface:

- Allows users to submit complaints regarding online financial content.
- Collects necessary information such as user details, description of the complaint, and any supporting evidence.

2. Complaint Database:

- Stores all submitted complaints along with relevant details such as user information, complaint description, and timestamps.
- Organizes complaints for efficient retrieval and management.

3. Complaint Review Engine:

- Analyzes submitted complaints to determine if they meet the criteria for severity identification.
- Utilizes natural language processing (NLP) techniques to extract key information from complaint descriptions.
- Determines whether additional information is required for proper evaluation.

4. Severity Identification Module:

- Evaluates the severity of each complaint based on predefined criteria.
- Classifies complaints into low severity and high severity categories.
- Utilizes machine learning algorithms to enhance accuracy in severity identification over time.

5. Resolution Management System:

- Manages the resolution process for each complaint based on its severity.
- Routes low severity complaints to the appropriate resolution pathway for quick resolution.
- Handles high severity complaints by initiating further investigation or escalation.

6. Notification System:

- Notifies users about the status of their submitted complaints.
- Sends alerts to relevant stakeholders when high severity complaints are identified or resolved.

- Discussion of findings and insights.

IV PROPOSE SYSTEM & IMPLEMENTATION

In this work, we introduce the *Financial Complaints* dataset (*FINCORP*), which unlike the *Complaints* and *Product Review* datasets, is a balanced dataset with nearly equal percentage of complaints (50.13%) and noncomplaints (49.87%) samples. Unlike the other two datasets, which contain generic complaints from various domains, our dataset focuses on grievances arising between financial institutions and consumers on the social media network Twitter. Another unique feature of our dataset is that, in addition to the complaint identification axis, we have expanded the dataset on three other closely related axes (severity level classification, sentiment classification, and emotion recognition) to better understand the nuances of the complaint identification task. To the best of our knowledge, this is the first gold standard complaint dataset specifically dealing with Financial complaints.

We create a word cloud to graphically depict the frequency of words that appear more frequently in complaints expressed on Twitter. The more frequently a term occurred in the complaint tweets, the larger the term is in the image. Figure 1 depicts the top 100 terms used by 6282 Twitter users to convey their dissatisfaction. If we observe the proposed system closely, we will see that Twitter users complain more
frequently using key phrases like response, refund, and please, alongside other words like RBI, fraud, and help. Table I shows the details of various existing and proposed CI-related datasets.

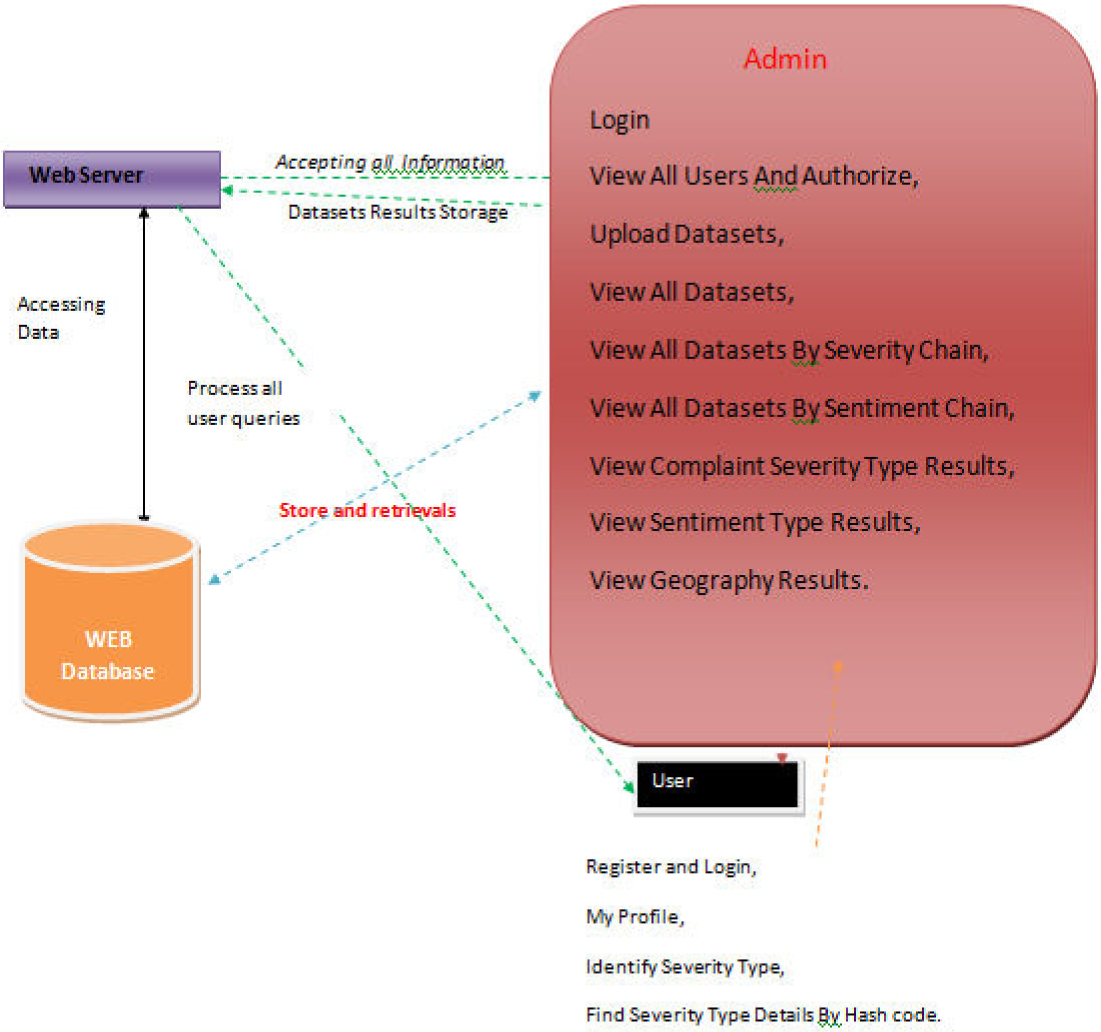
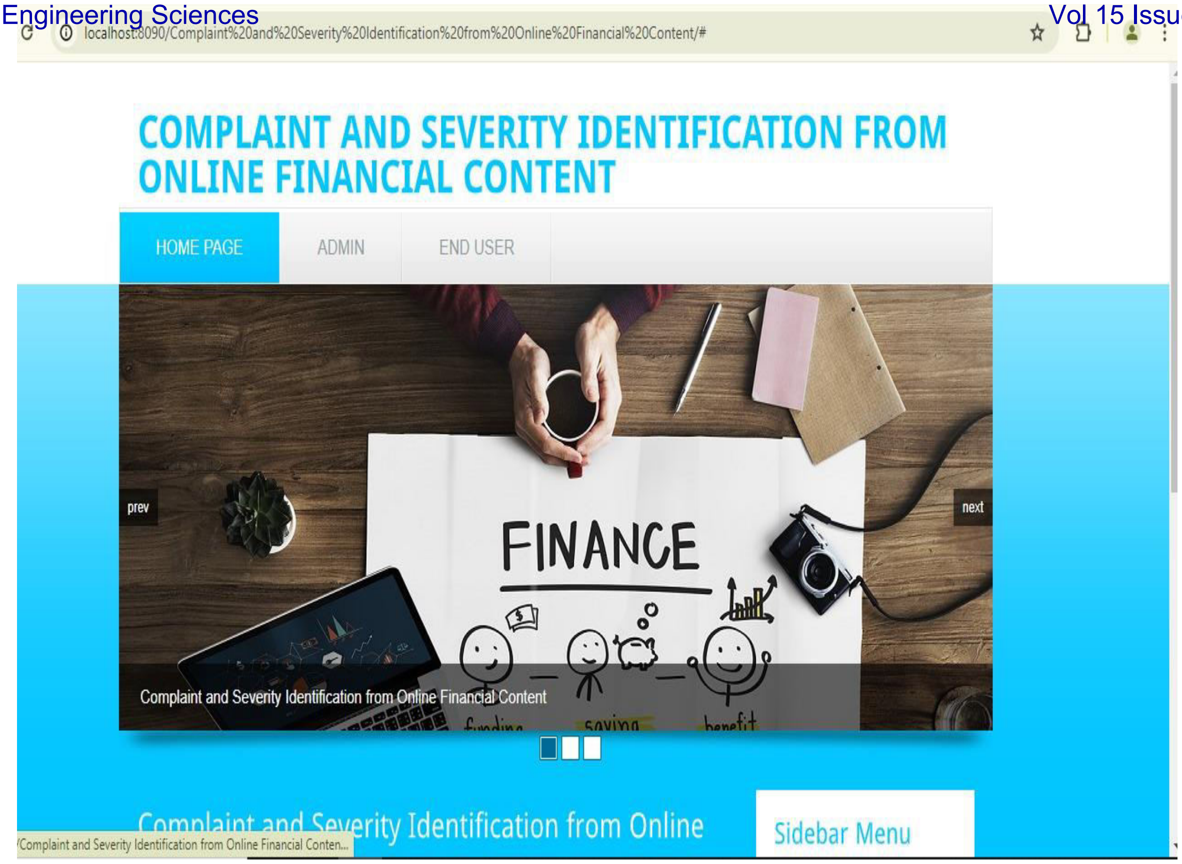


Figure 1: Proposed system architecture

V RESULT ANALYSIS

Home Page:



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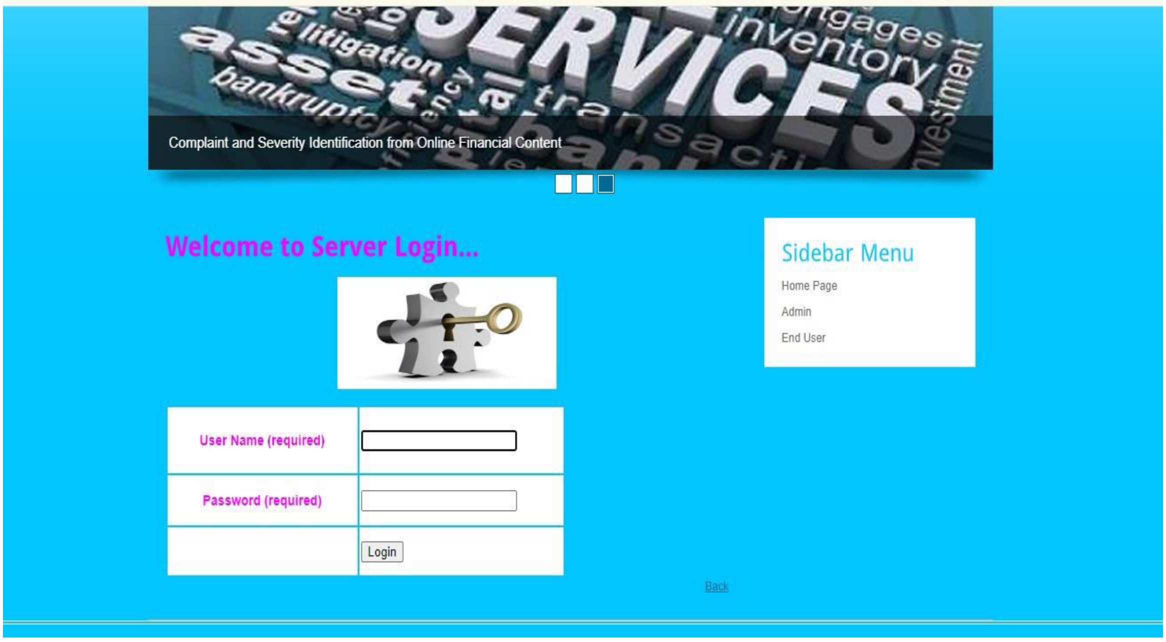

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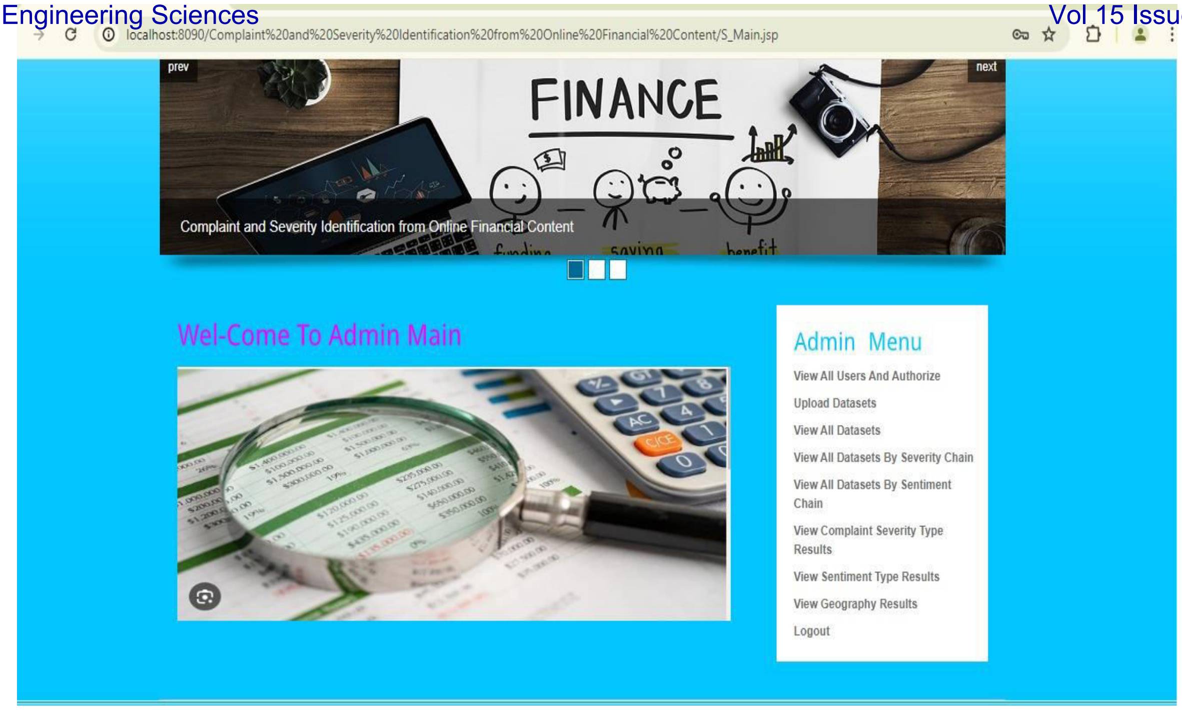

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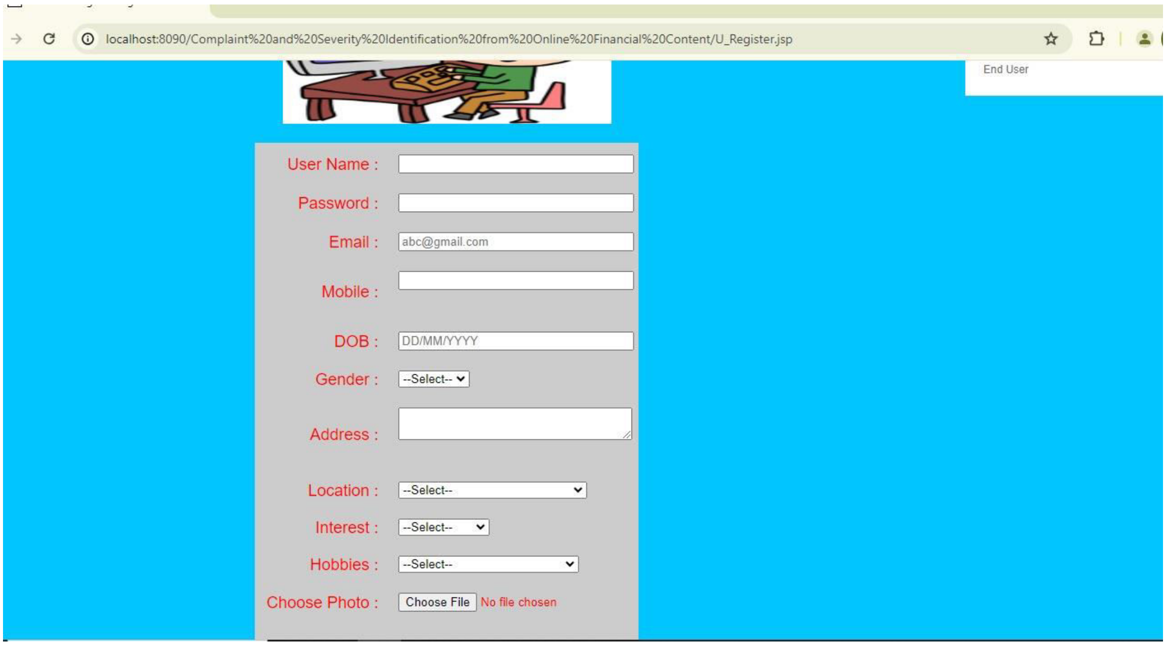

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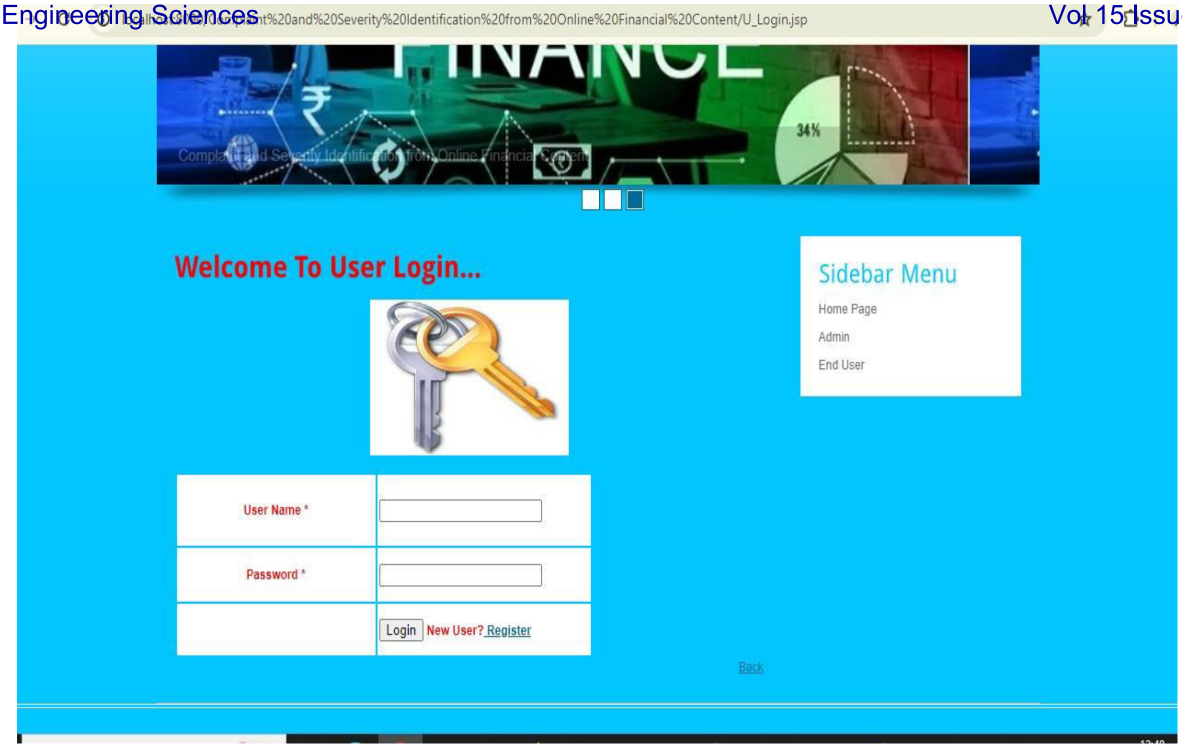

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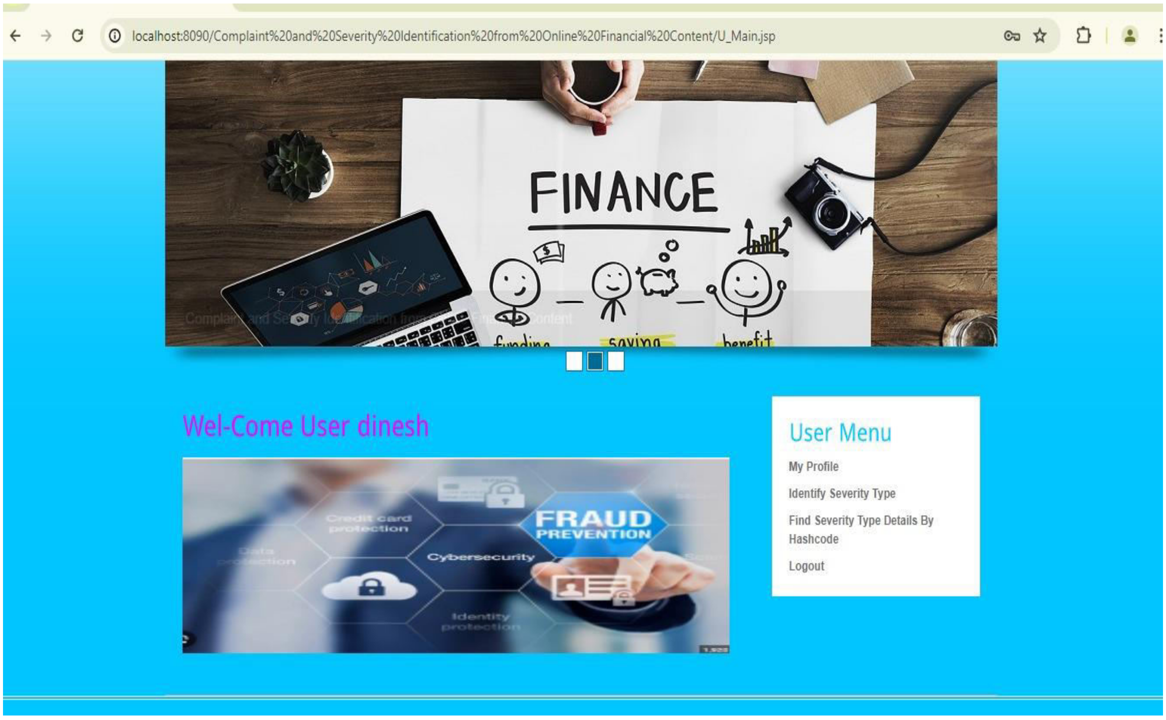

VI CONCLUSION

In this work, we have introduced FINCORP, an annotated dataset of complaints originating between financial institutions and consumers on Twitter. We have addressed the task of complaint identification and severity level prediction (primary tasks) jointly using a multi-task framework assisted by emotion and sentiment detection as auxiliary tasks. The paper goes into a detailed description of the dataset and the complete process of creating it. Every instance in the FINCORP dataset has been annotated across four axes: complaint, severity level, emotion, and sentiment classes, resulting in a dataset with a lot of diversity. We evaluated the dataset and reported the findings using several single-task, multi-task and other existing baselines. Given the scarcity of task-specific (complaint identification) data in English and even some low-resource languages, we believe this dataset would add value to social media analytics research and practice. We plan to expand our work in complaint identification at the sentence level in english as well as code-mixed languages in the future. Furthermore, the annotated corpus can aid research in other emotion and sentiment classifications tasks.

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