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Harnessing Ai to Gauge Citizen Emotions in Smart Cities

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Abstract- Over the past decade, smart city applications have gained significant attention in industrial informatics. However, little attention has been given to perceiving the emotions and perceptions of citizens who have a direct impact on smart city initiatives. We propose the use of publicly available, abundant social media conversations that contain contextual information encompassing citizens' emotions and perceptions which could be considered to provide the means to feel the 'emotional pulse' of a city. We propose an automated AI-based observation framework to detect the emergence of public emotions and negativity in conversations. We evaluated the applicability of the framework using 29,928 social media conversations towards the much debated topic of self-driving vehicles which will become increasingly relevant to smart cities. The patterns and transitions of citizens' collective emotions were modeled using the NLP and Markov models while the negativity (toxicity) in conversations was evaluated using a deep learning based classifier. The framework could be adopted by industry leaders and government officials for smart observation of citizen opinions to improve security, communication, and policymaking.

Keywords: Smart Cities, Industrial Informatics, Social Media Analytics, Citizen Emotions, Emotion Detection, Sentiment Analysis.

I. INTRODUCTION

Artificial Intelligence plays a significant role in identifying and interpreting human emotions from structured and unstructured data sources. Techniques such as Natural Language Processing (NLP), Machine Learning (ML), Deep Learning, and Sentiment Analysis enable systems to detect emotions like happiness, anger, fear, sadness, and satisfaction from textual, audio, and visual data. By applying these technologies in smart cities, governments and organizations can better understand public sentiment regarding city services, policies, infrastructure, and social events.This research paper focuses on harnessing AI to gauge citizen emotions in smart cities by utilizing intelligent data analysis techniques.

The proposed approach aims to collect and process citizen-generated data from multiple platforms and apply AI-based sentiment analysis models to identify emotional trends in urban environments. Such analysis can help authorities make informed decisions, improve citizen engagement, predict social issues, and enhance the overall efficiency of smart city management.

II. LITERATURE REVIEW

P. Chakravarty, S. Gattupalli, U. Chakravarty, G. Chand, and W. Lee discussed the role of Artificial Intelligence (AI) and Data Analytics (DA) in improving earth resource management through advanced early warning systems and crisis communication. The study focuses on addressing the increasing challenges caused by climate change in highly vulnerable regions. The proposed approach integrates AI-based predictive models and data-driven communication systems to provide timely alerts and effective disaster response strategies. The research highlights how intelligent monitoring systems can support governments and organizations in minimizing risks, improving emergency preparedness, and ensuring sustainable resource management.[1].

S. Hassani, U. Dackermann, M. Mousavi, and J. L. presented a systematic review of data fusion techniques for optimized Structural Health Monitoring (SHM). The study explains how rapid advancements in sensing technologies, IoT devices, and data transfer systems have enabled the collection of large-scale structural data in real time.

The authors emphasized that integrating AI-driven models with edge computing and IoT sensors improves the efficiency and accuracy of monitoring systems. Various Machine Learning (ML) algorithms, including deep learning and ensemble methods, were analyzed to identify structural damage patterns and enhance predictive analysis. The results demonstrate that AI-integrated monitoring systems outperform traditional methods in adaptability and decision-making capabilities.[2].

M. Balduini, S. Bocconi, A. Bozzon, E. Della Valle, and Y. Huang proposed a case study on active, continuous, and predictive social media analytics for smart cities. The research introduces a recommendation system designed for large-scale city events, such as Milano Design Week, by analyzing the digital footprints of visitors on social media platforms. The framework combines deductive and inductive stream reasoning techniques with visitor-modeling functionality to semantically analyze social network activities. The system effectively provides personalized recommendations even when user preference information is limited. The study highlights the importance of AI-driven social media analytics in enhancing smart city services, improving visitor experiences, and enabling intelligent urban event management.[3].

D. Milne, C. Paris, H. Christensen, P. Batterham, and B. O'Dea discussed the importance of understanding citizens' emotions and perceptions in smart cities using Artificial Intelligence. The study proposes an automated AI-based framework that analyzes publicly available social media conversations to identify public emotions and negativity trends. The framework utilizes Natural Language Processing (NLP), Markov models, and deep learning-based classifiers to evaluate emotional transitions and toxicity in discussions related to self-driving vehicles in smart cities. The analysis was conducted using 29,928 social media conversations, demonstrating the effectiveness of AI in detecting collective emotional patterns. The research highlights how such systems can support policymakers and government officials in improving security, communication, and smart city governance.[4].

III. METHODOLOGY

This research proposes an AI-based framework to analyze and understand citizen emotions in smart cities using social media data. The system collects publicly available conversations from digital platforms and processes them using Natural Language Processing (NLP) and Machine Learning (ML) techniques. Sentiment analysis and toxicity detection models are applied to identify emotions such as positive, negative, and toxic behavior in public discussions.The framework utilizes algorithms such as Support Vector Machine (SVM), Random Forest, and deep learning-based classifiers to detect emotional patterns and analyze the collective emotional pulse of citizens. The extracted data is preprocessed, classified, and evaluated using performance metrics like precision, recall, and confusion matrix analysis to ensure prediction accuracy.The proposed methodology enables governments and smart city authorities to monitor public perceptions, improve decision-making, strengthen communication, and enhance urban governance through intelligent emotion analysis.

Disadvantages of existing system:

- Poor Interpretability.
- Less accuracy.
- Complex Implementation.

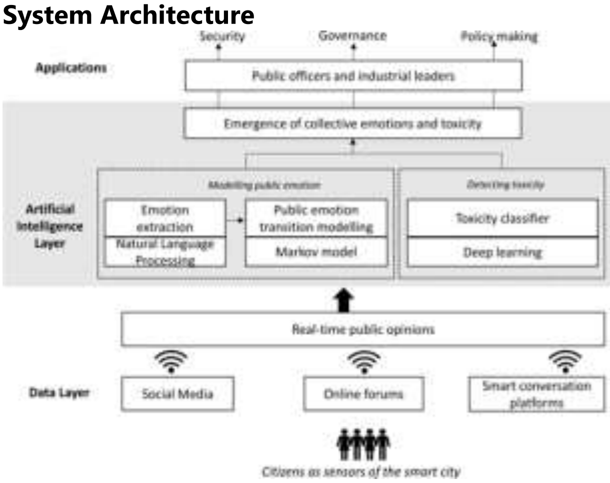
Proposed System

In proposed system AI-based emotion observation framework to monitor the emotions and perceptions of citizens via publicly available social media data. Using Twitter responses towards self-driving vehicles, we demonstrated how the emotions and negativity emerge during an incident and shift over time. We used a combination of NLP, Markov models, and deep learning to create emotion modeling and toxicity detection capabilities. Compared to traditional survey opinions, social media data have numerous advantages as they capture publicly available, frequently updated and voluminous data, which are enriched with openly expressed emotions and feelings of citizens.

Advantages Proposed System Advantages

- High Prediction Accuracy
- Handles Missing Data Automatically.
- Fast Training and Scalability.
- Feature Importance Ranking.

System Architecture



The proposed architecture collects citizen opinions from social media platforms and processes the data using Natural Language Processing (NLP) techniques. Machine Learning models such as SVM and Random Forest analyze the data to detect emotions, sentiments, and toxic behavior. The generated insights help smart city authorities understand public emotions and improve decision-making and urban governance.

MODULES:

1) Smart city applications and citizens: The design and the conceptualization of a smart city necessitate several factors including technology, policies, economy, governance and people communities . As the current approaches in smart cities strive to create an allconnected environment it is imperative to understand the smart initiatives from citizens' perspective which would be helpful for policymakers and industrial leaders when developing future strategies. Although citizen engagement is known as a key component in most definitions of smart cities, limited research has been carried out to investigate the practicality and applicability of understanding public participation. Given the proliferation of content generated via social media and the increasing security threats, it is also important.

2) Use of social media to extract emotions and sentiments: Several attempts have been made to detect emotions from social media in a smart city environment. Guthier et al present an approach to detect emotions from Twitter posts and visualize the emotions on a geo map based on the locations extracted from the post. Sentiment analysis using social media in the context of smart cities has been carried out by Li et al where they used a Multinomial Naïve Bayes classifier to classify sentiments of Twitter posts for governance applications. Doran et al, propose the use of social media to extract perceptions of citizens using a probabilistic language model using geo-tagged Twitter posts. Similar approaches have been suggested to extract sentiments from Twitter for smart city applications, extract emotions from technical sensors and crowdsourced data sources to support urban planning and the applicability of social media analytics for smart cities. Generally, emotion monitoring via social media has been used for different objectives in different disciplines.

IV. IMPLEMENTATION

AI-based emotion observation framework to monitor the emotions and perceptions of citizens in a smart city environment. The proposed framework collects data from social media and other conversation platforms which are made public. Next, emotional expressions are extracted from the collected social media contents. The extracted emotions are then used to generate an emotion transition model indicating the emotion changes.Further, social media conversations are used to detect the presence of negativity by identifying different levels of negativity among citizens. These capabilities are integrated into the AI approach (AI Layer) which generates outcomes to denote the emergence of public emotions and toxicity which are useful for strategic decision making related to smart cities. The data layer is able to collect data from public social media channels, online discussion forums, and smart conversation platforms such as chatbot applications and smart assistant applications. For demonstration purposes, we have presented outcomes using Twitter data. We propose that the data layer can be developed to integrate multiple sources of data in a real-time manner.

V. EXPERIMENTAL RESULTS

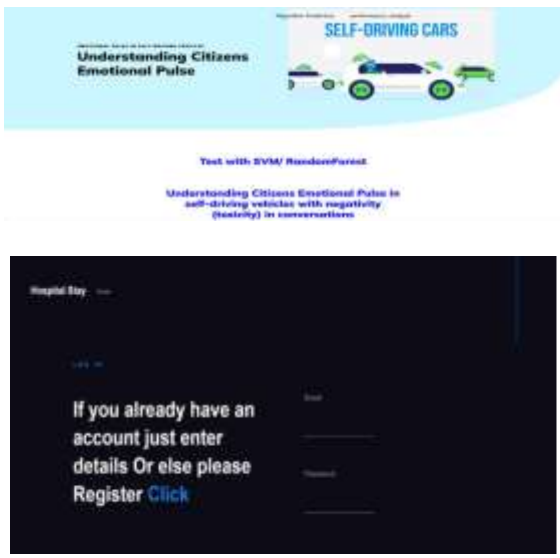


Figure: Home Page

- This image shows the home interface for the “Harnessing AI to Gauge Citizen Emotions in smart Cities” web application.

Figure: Input Page

• The page allows users to enter a sentence or tweet into the text box and test whether the content expresses a positive, negative, or potentially toxic sentiment. After clicking the TEST button, the system processes the input text using Natural Language Processing (NLP) techniques and predicts the sentiment category based on the trained machine learning model.

Figure: Result Page

- This page represents the performance evaluation of the machine learning model used for sentiment and toxicity prediction in conversations related to self-driving vehicles. The system evaluates how accurately the algorithm classifies text into Positive and Negative sentiment categories.

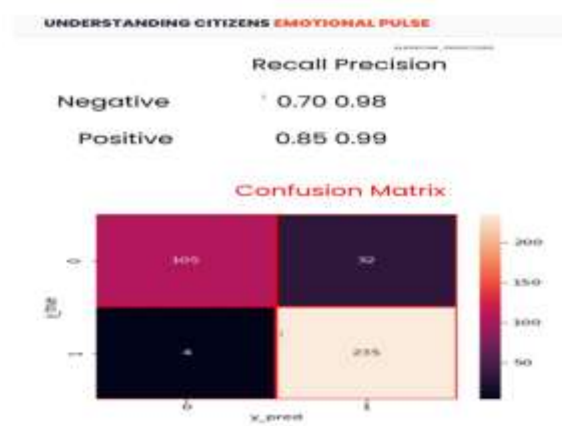


Figure: Precision Page

- The page displays important evaluation metrics such as Recall, Precision, and a Confusion Matrix, which help measure the effectiveness of the trained model.

VI. CONCLUSION

In this paper, we presented an AI-based emotionobservation framework to monitor the emotions and perceptions of citizens via publicly available social media data. Using Twitter responses towards self-driving vehicles, we demonstrated how the emotions and negativity emerge during an incident and shift over time. We used a combination of NLP, probabilistic models, and deep learning to create emotion modeling and toxicity detection capabilities of the proposed framework. By developing and evaluating this AI framework, we enable the capture and representation of the emotional pulse ofthe city.

We position this among pioneering studies to use AI to capture citizens' emotional pulse from digital data channels, thus create an overview of citizens' emotions related to smart city initiatives. Compared to traditional survey opinions, social media data have numerous advantages as they capture publicly available, frequently updated and voluminous data, which are enriched with openly expressed emotions and feelings of citizens. This will serve as a strong foundation to utilize data via social media and other smart conversation platforms for representing citizens' emotions. The outcomes and the capability of using AI for understanding citizens' emotional pulse have the potential to inform strategy development and policymaking for industrial leaders as well as for elections, political campaigns, and governance.

VII. FUTURE ENHANCEMENT

Future enhancements to the framework, we propose experimenting with heterogeneous sources of data to compare and contrast the overall emotional behaviors of citizens in different social media platforms and investigate information diffusion in digital data channels. As limitations of the study we acknowledge the need for advanced language modelling to handle expressions related to sarcasm, irony and humor. One of the main limitations in using social media data for smart city initiatives is resolving the residency of the user.

We recommend using advanced geographical location extraction and filtering techniques for this purpose. Furthermore, the social media data extraction could be improved by including features to detect fake content generated by automated bots. In addition, applying the functionalities of this framework to monitor a series of events would enable to monitor the changes and cascading effects of citizens' emotions over time. However, using the framework in smart city specific conversation platforms will omit limitations related to noisy data and provide a more concise view of city's residents.

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