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Using Artificial Intelligence to Monitor the Emotional Pulse of Smart City Residents

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ABSTRACT

Industrial informatics has been paying increasing attention to smart city applications during the last decade. However, individuals' emotions and impressions, which have a direct influence on smart city programmes, have gotten little attention. A city's 'emotional pulse' may be gauged via the use of publicly accessible, plentiful social media discussions that include contextual information about residents' feelings and perspectives. Emotions and negativity may be detected using an automated AI-based observation system. As self-driving cars become more prevalent in smart cities, we used 29,928 social media chats to gauge the framework's applicability. The NLP and Markov models were used to predict the patterns and transitions of citizens' collective emotions, and a deep learning-based classifier was used to assess the negativity (toxicity) in talks. In order to increase security, communication and policymaking, business executives as well as government authorities may use this framework.

Keywords- Artificial intelligence, smart city, emotional pulse.

1. INTRODUCTION:

As a result, the concept of "smart cities" is based on the development of sophisticated, automated, and networked intelligent industrial applications [1]. There has been a lot of focus on smart applications in the context of a smart city, but little attention has been made to the fundamental thing that keeps a city going, its residents [2]. It is critical to use artificial intelligence (AI) to comprehend the emotions and perceptions of people toward industrial applications as intelligent industrialisation progresses toward what has been dubbed the "fourth industrial revolution." This recognition of the citizens' viewpoint may be seen even in cognitive automation, where it is said that many smart programmes depend on the subjective desires of their users [3]. The use of sensors offers privacy and administrative issues when it comes to continuous monitoring, despite efforts to quantify individuals' emotional responses using physical sensors [4]. The views and emotional responses of residents, which continually affect smart city efforts, cannot be sensed by such physical sensors [5]. Despite this, people use social media every day to voice their thoughts, insights, and impressions. Using publicly accessible data sources such as social media, it is possible to develop smart observation systems that allow one to sense the "emotional pulse" of a city via the collective feelings expressed by inhabitants.

When individuals' emotions, sentiments, and ideas are reflected in the huge volumes of data created by social media, it becomes an invaluable resource for policymakers. The quantity of data created on social media may be considered as a 'big data' source that captures the voice of people [6] because of its exponential expansion. One way to get a feel for the emotional pulse of a country is to utilise social media platforms, which have vast reservoirs of user-generated data [6, 7]. Understanding how residents feel about the smart city environment and its applications is a goal of this research, which incorporates emotional pulse concepts. In order to build future breakthroughs and policies, it is critical to comprehend and'sense' people' perceptions [8] since all smart applications are designed around and with the objective of serving residents better. However, despite its relevance, the use of citizen opinion and emotional responses connected to smart

city applications is now confined to sentiment and emotion extraction, and does not take into account the development and shift of emotional reactions via social media data.
First, we propose the first practical application of social media to capture the pulse of a smart city by building an AI-based emotion observation framework that uses free-flowing social media information to identify the emotional pulse of residents in a smart city setting. An emotional pulse of inhabitants may be monitored via social media interactions, allowing for an examination of public opinion and how it changes over time, in a smart city environment.

2. Citizens and smart city applications

Technology, policy, economics, governance, and human groups all play important roles in the creation and conception of smart cities [8]. A better understanding of residents' perspectives on existing smart city efforts is critical for politicians and industry leaders when establishing future plans.... Many definitions of smart cities emphasise citizen involvement, but little research has been done to examine the feasibility and application of this concept [9].

Smart solutions that monitor inhabitants' well-being in a smart city setting are also necessary because of the growth of social media material and the rise in security concerns. More than 100,000 Twitter accounts have been blocked for terrorist activities [10] in the last year, according to Reuters, demonstrating the need of an emotion surveillance system for a smart city environment even from a security standpoint. With this information, industry executives may better grasp the public's view and take preventative steps in the event that it is required.

In a smart city, there have been many efforts to identify emotions from social media. On the basis of the locations derived from the post, Guthier et al. offer a strategy to identify and depict emotions from Twitter tweets [11]. An effort to analyse sentiment in the context of smart cities has been made by Li et al [5] who utilised an algorithm to categorise the sentiment of Twitter tweets for governance purposes. Using a probabilistic language model, Doran et al. suggest the use of social media to extract people' impressions using geo-tagged Twitter messages. Twitter sentiments may be extracted for smart city applications [12], [13], [14], and [15],[16] in similar ways. Social media analytics can also be used for smart city applications [15],[16] in similar ways. Emotion tracking on social media has been utilised for a variety of purposes across a wide range of fields.

The aforementioned methods are geared at collecting sentiments and feelings from social media, but they do not aim to model emotions in order to get an understanding of people' collective emotions. There should be more than just a focus on emotion detection when trying to understand the sentiments of the general public; instead, we believe the focus should be on computational models to represent the diversity of feelings and emotions expressed across regions, populations, sectors of the economy, and ethnicities as a whole. We believe that an understanding of a city's 'emotional pulse' may be derived from an analysis that results in such awareness[17-20].

3. Problem definition

When individuals' emotions, sentiments, and ideas are reflected in the huge volumes of data created by social media, it becomes an invaluable resource for policymakers. The quantity of data collected on social media may be considered as a "big data" source that captures the voice of people due to the exponential expansion of social media. As a nation's 'emotion pulse' is defined as the sum of its residents' feelings, it is possible to acquire insights about their well-being via the usage of social media.

Research Contribution: In order to better understand how residents see the smart city environment and apps, we apply the notion of emotional pulse to the smart city setting. For the sake of better serving residents, it is critical to comprehend and'sense' the perspective of citizens in order to build new technologies and policies in the future. However, despite its relevance, the use of citizen opinion and emotional responses connected to smart city applications is now confined to sentiment and emotion extraction, and does not take into account the development and shift of emotional reactions via social media data.
System Recommendation

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Natural Language Processing (NLP) is used to extract emotions from social media information. Probabilistic models are used to predict the public's emotional changes, and deep learning is used to determine the amount of toxicity. A hotly discussed use of self-driving cars in smart cities is used to illustrate the framework's applicability in that setting. We used Twitter reactions to do so.

Algorithms:

The next section focuses on algorithms.
Random forest, Decision Tree, LSTM, Naive Bayes, and XGBoost are all used in this research.

Document categorization, time series analysis, and voice and speech recognition are just a few of the many applications for LSTM, a specific sort of RNN. There is a difference between feedforward and recurrent neural networks (RNNs). RNNs are seldom used in experimental studies because of a few flaws that lead to inaccurate predictions.
To tackle the issue, LSTM utilises a set of gates that can be used to forget and learn new knowledge. A cell, an output gate, and a forget gate make up a typical LSTM unit. In order to recognise values at random intervals, the cell relies on its gates, which are responsible for regulating the flow of information into and out of the cell.

It uses a three-pronged approach: random data selection, feature selection, and basic decision tree splits that only take into account a portion of all characteristics. Each tree in a random forest learns from a random sampling of data points during training data. A random forest model is the result of a large number of decision trees. The model just averages the expected outcome of trees, which is dubbed a forest. Each basic decision tree's splits are based on a random subset of all variables rather than a full set, and the training data used to build the trees is selected at random when the trees are formed. During the random forest training process, every basic tree learns from a random sample of the dataset.
When compared with more advanced algorithms, a Naive Bayes classifier may be very quick. Class distributions can be evaluated as one-dimensional distributions because of the separation of the distributions. As a result, the dimensionality curse is less of a burden.
Classifiers based on Bayes' theorem with strong independence assumptions between features given the class variable are known as naive Bayes classifiers. A collection of supervised learning algorithms are used in this strategy.

The goal is to build a model that can predict a target value by learning simple decision rules derived from the data attributes. Some benefits of employing this approach include the ability to solve issues with several outputs, as well as the ease with which it may be interpreted and understood.
Networks based on Recurrent Neural Networks
RNNs are a well-known type of neural networks that are used in a variety of applications. It is common for input to be routed through many layers of the neural network before being converted to output. Two successive inputs are supposed to be completely independent, although this isn't true for all processes. For example, if you want to predict the stock market for a certain time period, you need to look at previous data.
Advanced neural networks, such as Recurrent Neural Networks (RNNs), are capable of processing extended sequences because of their internal memory. When it comes to long-term forecasting of stock prices, RNN is a great fit. Recurrent Neural Networks (RNNs) may outperform neural networks when it comes to predicting outcomes.
XGBoost
XGBoost is an efficient, versatile, and portable gradient-boosting library. Gradient Boosting develops machine learning techniques. Many data science problems can be solved quickly and accurately using XGBoost's parallel tree boosting (GBDT, GBM).

It's time to test each algorithm's performance once we've trained them all. Emotional Pulse will utilise the most accurate algorithm mentioned in fig-1 and Fig2.
Using the most accurate algorithm, we can then input the user's information to get an accurate prediction of their Emotional Pulse.

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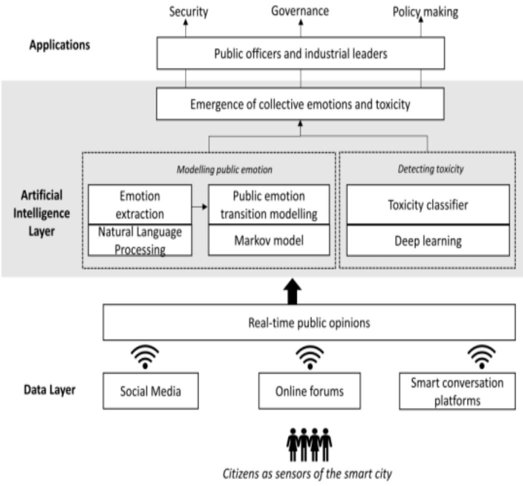

Fig-1 : Architecture/Framework:

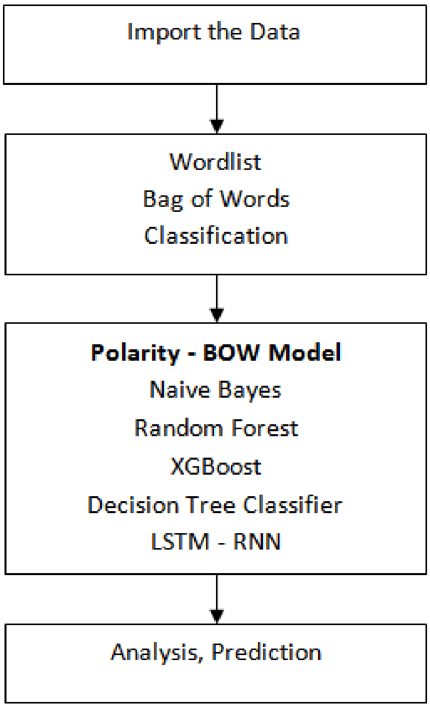

Fig-2: Algorithm and Process Design

4. Information gathering

We analysed Twitter replies to current situations in order to better understand how individuals feel about them.
Metrics for Evaluation:
Accuracy and Receiver F1-Score Our models are evaluated using operating characteristics-area under the curve (ROC-AUC) criteria. False Positive Rate (FPR) must be taken into account while computing F1-score and Accuracy.
True Positive Rate (TPR)
Accuracy
Precision
Recall
F1-score
True positive (TP) is defined as the number of occurrences that were properly identified.
An incorrectly predicted or unneeded number of occurrences is referred to as a false negative (FN).

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An FP is a number of occurrences that were wrongly anticipated.
True negative (TN): The number of occurrences that were predicted accurately but were not necessary.
The percentage of false positives: Accuracy metrics may be used to evaluate how well machine learning works.
FPR = FP/(FP+TN)/(FP+TN)

TPR is defined as TPR=FP/(FP+TN) since it is a synonym for recall.
Accuracy: To quantify performance, just divide the number of accurately predicted observations by the total number of expected observations.

Accuracy=(TN+TP)/(TP+FP+TN+FN)
In the original data, it is the ratio that properly predicts positive observations out of all of the original observations.

TP/(TP+FN) = TP/(TP+FN) = Recall.
It is used to compute the right values that have been identified with precision. A software's positive predictive value may be calculated by subtracting all of the software's negative predictive values from the overall positive predictive values. Precision is defined as TP/(TP + FP) = TP

F1-score: Model accuracy and recall are combined in the F-score, which is defined as the model's mean precision plus recall. The F-score is another name for it. F1 Score = 2 (Precision Recall/Precision + Recall) is how it is calculated.

Based on prediction scores, the area under the curve of prediction scores known as ROC-AUC may be determined.

5. Results and Discussion

Using python programming and the various artificial intelligence technique the following results has been obtained Detailed overview has been presented in form of graph and tables FIG-3 TO Fig-15.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   tweet_id                      14640 non-null  int64
 1   airline_sentiment             14640 non-null  object
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object
 6   airline_sentiment_gold        40 non-null     object
 7   name                          14640 non-null  object
 8   negativereason_gold           32 non-null     object
 9   retweet_count                 14640 non-null  int64
 10  text                          14640 non-null  object
 11  tweet_coord                   1019 non-null   object
 12  tweet_created                 14640 non-null  object
 13  tweet_location                9907 non-null   object
 14  user_timezone                 9820 non-null   object
dtypes: float64(2), int64(2), object(11)
memory usage: 1.7+ MB
```

Fig-3 : data training

	Id	Tweet
0	6.289494e+17	dear @Microsoft the newOoffice for Mac is grea...
1	6.289766e+17	@Microsoft how about you make a system that do...
2	6.290232e+17	Not Available
3	6.291792e+17	Not Available
4	6.291863e+17	If I make a game as a #windows10 Universal App...

Fig-4: Data testing

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```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9968 entries, 0 to 9967
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Id      4000 non-null   float64
 1   Tweet   4000 non-null   object
dtypes: float64(1), object(1)
memory usage: 155.9+ KB
```

Fig-5 Data analysis

```
<AxesSubplot:xlabel='airline_sentiment', ylabel='count'>
```

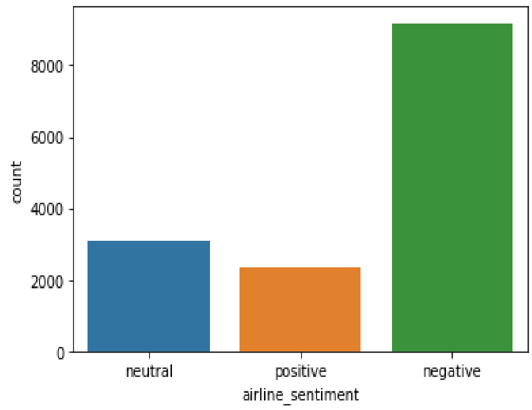

Fig-6: Data visualization

```
0                                            What said
1    plus youve added commercials to the experience...
2    I didnt today Must mean I need to take another...
3    its really aggressive to blast obnoxious enter...
4              and its a really big bad thing about it
Name: text, dtype: object
```

Fig-7: Data cleaning

```
---------------------------------------------------------
Testing BernoulliNB
Learing time 1.455106496810913s
Predicting time 0.6515891551971436s
=================== Results ===================
            Negative     Neutral     Positive
F1       [0.85008818 0.57301499 0.6351866 ]
Precision[0.82988981 0.59515571 0.67149758]
Recall   [0.87129429 0.55246253 0.60260116]
Accuracy 0.7611566484517304
===============================================
```

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Fig-8 :Random Forest classifier

```
--------------------------------------------------------
Testing RandomForestClassifier
Learing time 83.41114258766174s
Predicting time 1.8760335445404053s
=================== Results ===================
            Negative     Neutral     Positive
F1       [0.84316142 0.54254144 0.60170147]
Precision[0.82161235 0.56050228 0.64725458]
Recall   [0.86587129 0.52569593 0.56213873]
Accuracy 0.7456739526411658
==============================================
```

Fig-9: XGBoost classifier

```
--------------------------------------------------------
Testing XGBClassifier
Learing time 359.2737820148468s
Predicting time 0.6608796119689941s
=================== Results ===================
            Negative     Neutral     Positive
F1       [0.82091178 0.35909446 0.55947955]
Precision[0.72056815 0.66282421 0.78385417]
Recall   [0.95372379 0.24625268 0.4349711 ]
Accuracy 0.7215391621129326
==============================================
```

Fig-10: Decision Tree Classifier

```
--------------------------------------------------------
Testing DecisionTreeClassifier
Learing time 17.9675116539001465s
Predicting time 0.07171750068664551s
=================== Results ===================
            Negative     Neutral     Positive
F1       [0.79544201 0.49260581 0.52098408]
Precision[0.80897196 0.47030185 0.52173913]
Recall   [0.78235719 0.51713062 0.52023121]
Accuracy 0.6846539162112932
==============================================
```

Fig-11: LSTM – RNN

```
[[   0    0    0 ... 3560  364  141]
 [   0    0    0 ...   76  196  754]
 [   0    0    0 ...  304   79  354]
 ...
 [   0    0    0 ...   48   50    1]
 [   0    0    0 ...   32   57  353]
 [   0    0    0 ...    3 4197  569]]
```

Fig-12: data training 1

```
[    0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0   13  143 1590  549   57  122  660  221 2105
    59  752   57  428   20    3  257  855    4  224   81 5034 3559 5035
  2830 3560  364  141]
```

Fig-13: data training 2-Tensor flow model

```
[[    0    0    0 ...   10    1   18]
 [    0    0    0 ...   48   50    1]
 [    0    0    0 ...    2 6450  529]
 ...
 [    0    0    0 ...   99    3  314]
 [    0    0    0 ... 1542   91    1]
 [    0    0    0 ...  200  106   30]]
```

Fig-14: data training 2-BOW model

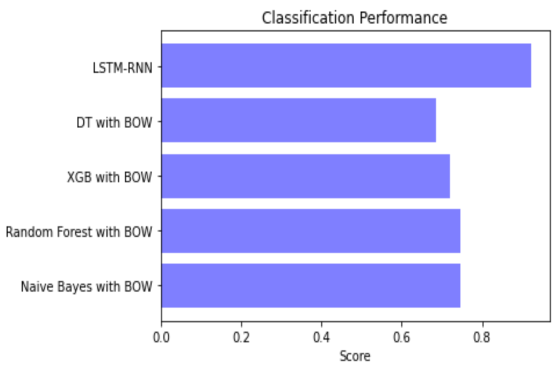

Fig-15: Polarity BOW model and LSTM

Here we used Polarity BOW model with mergering with Machine learning for analysis and then we use LSTM for same data finally comparing which is giving better accuracy for user prediction .

6. CONCLUSION

Using publicly accessible social media data, we developed an AI-based emotion observation framework to keep tabs on people' feelings and impressions. We looked studied how people's feelings towards self-driving cars changed over time based on their tweets about them. The proposed approach uses a mix of NLP, probabilistic models, and deep learning to model and identify emotions and toxins. We are able to collect and portray the city's emotional pulse via the development and evaluation of this AI framework. We believe this is one of the first studies to employ AI to gather people' emotional pulses from digital data sources and thereby provide an overview of citizens' emotions connected to smart city efforts. There are various benefits to social media data, such as their ability to collect public, often updated and abundant data as well as the freely stated thoughts and sentiments of residents, compared to conventional survey responses. This will serve as a solid basis for depicting individuals' emotions using data from social media and other intelligent discussion platforms.

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