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SMART Dashboard: A Key To Social Media Success With Data-Driven Decisions

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ABSTRACT –

The SMART dashboard is an excellent tool for monitoring and analyzing social media activity, notably Twitter messages in specific cities. This tool traces information diffusion on critical topics at the municipal level, for example, flu outbreak, drug abuse, or epidemics. SMART goes beyond data collection, providing automated data processing to filter out noise—these redundant retweets—and refine precision analysis through machine learning. Such data will enable researchers to run spatiotemporal analyses with regards to issues under study about their spread and impact over time and across locations in the city. Besides, SMART has a data visualization component that represents the results of trends for the week and month, setting out metrics such as top URLs, retweets, mentions, and hashtags. In this way, it delivers a comprehensive package for understanding public sentiment, how misinformation is spreading, and community responses—information crucial to researchers, public health officials, and policymakers. SMART dashboard also has a high scope in future for Data scientists to analyze the impacts that are happening around the globe.

Keywords – SMART dashboard, social media monitoring, Spatiotemporal analysis, Public sentiment, Data visualization.

Introduction :

The SMART Dashboard is a sophisticated tool used to monitor and analyze activity on social media, particularly tweets in selected cities. Through this tool, researchers, public health officials, and policy makers are able to monitor and track the spread of information about pressing issues, such as flu outbreaks, drug abuse, and epidemics. By not stopping at mere data accumulation, SMART deploys real-time automated data processing for filtering out unnecessary information such as redundant retweets, and then uses these data to enhance analysis precision through machine learning algorithms. One of the distinctive capabilities of the SMART Dashboard is its spatiotemporal analysis, through which it enables users to understand how specific issues spread and evolve over time and in space within urban areas. Its advanced data visualization tools provide insights in clear, actionable formats into weekly and monthly trends with top metrics such as URLs, retweets, mentions, and hashtags. It gives a comprehensive near real-time view of the sentiment of the public, spread of misinformation, and response of the community. The current usages are just a scratch on the surface. Research possibilities are enormous. Using this platform, data scientists could understand the global implications of social phenomena. Such a tool would be precious for the academic, government, and non-profit spheres.

LITERATURE SURVEY :

The following research papers are studied in details to understands the proposed recommendation technique and experimental result for predicting the output

Zaballa et al. (2022) also employed several algorithms in combination to enhance the data processing ability in SMART Dashboard in the analysis of social media responses to COVID-19 [1]. Sentiment analysis brings public emotions in social media posts to classify public emotions about such events with the help of classifiers, such as Naive Bayes and Support Vector Machines. More than that, NLP methods such as ***TF-IDF***, ***LDA*** for topic modeling, and Named Entity Recognition extract and classify information about COVID, enabling data to be grouped by theme and categorized. Tools such as Z-score analysis and density-based clustering (DBSCAN) are used to identify anomalies in post frequency or sentiment that might indicate an uptick in misinformation or a change in public interest. Finally, time series analysis and STL decomposition are supplemented with exponential smoothing so that refinement of trend analysis maps time-related changes in the social discourse. Together, these algorithms produce a textured view of public response to COVID-19, revealing critical real-time insights on community sentiment, behavior, and emerging concerns.

This paper [2] describes, social media-based intelligence applied for smart cities in disaster response and management. The authors discussed how real-time data from social media can be used in different ways, including situational awareness, early warnings, and communication in the aftermath of disasters. Hence, the debate is using AI/ML tools on vast amounts of streaming, unstructured data, say from Twitter or Facebook, and transiting those into insight. According to the authors, some of these issues include noise filtering, data accuracy, and scalability of systems at a disaster site under high-stress conditions, among others. It targets smart city infrastructures and develops sophisticated AI and ML techniques that should automate disaster detection, tracking of information dissemination, and provide support for resource allocation in the most effective way. The present work falls within the emerging literature focusing on either the application of social media, intelligent systems, or both, in promoting urban resilience, disaster mitigation, and smart city management.

In the paper [3] *"Location-centric social media analytics: Challenges and opportunities for smart cities"* by Yang, Qu, and Cudre-Mauroux (2020), various machine learning techniques are utilized to analyze location-based social media data for smart city applications. ***Natural Language Processing (NLP)*** methods, including ***sentiment analysis***, help categorize text data and assess public opinion, while spatial clustering algorithms, such as ***DBSCAN***, group location-based posts to detect hotspots and areas of recurring issues. Topic modeling, with techniques like Latent Dirichlet Allocation (LDA), identifies dominant themes within content, enabling structured analysis of relevant urban issues. Time-series analysis is also applied to track trends over time, which assists in forecasting future events and understanding seasonal patterns. Together, these techniques allow for more accurate, context-aware, and relevant social media data insights, aiding city planners in making informed decisions and improving urban living.

The study *Image4Act* [4] presents a pioneering framework that addresses the need for real-time processing and analysis of social media images shared during crisis events such as natural disasters. This system utilizes advanced computer vision and machine learning techniques to transform unstructured image data into actionable insights, significantly enhancing disaster response efforts. The framework's core functionality revolves around the use of Convolutional Neural Networks (CNNs), which play a pivotal role in classifying images based on their content. These networks are highly effective in identifying and categorizing visual elements, such as infrastructure damage or ongoing relief activities, providing emergency responders with critical information at a glance. Moreover, the framework incorporates cutting-edge object detection algorithms, including R-CNN and YOLO, to mark and extract specific objects from images. These objects could range from damaged structures to emergency vehicles or equipment, offering granular insights that are invaluable for on-ground relief teams. By integrating these advanced techniques, *Image4Act* not only enables real-time situational awareness but also empowers emergency responders to prioritize tasks and allocate resources more efficiently. The system's ability to rapidly process and interpret social media imagery ensures that decision-makers can differentiate between urgent and non-urgent needs, reducing delays and optimizing response strategies. In addition to its technical strengths, the framework highlights the transformative potential of combining social media data with machine learning models. This integration allows for a dynamic, data-driven approach to disaster management, where vast amounts of information can be processed and analysed in real-time to inform critical decisions. By providing timely insights into the scale and nature of a disaster, *Image4Act* supports proactive measures, helping mitigate the impact of crises on affected populations. The system represents a significant advancement in leveraging modern technology for humanitarian purposes, offering a robust tool for improving disaster response and resource management in challenging environments.

The investigation of Dashboard Design Patterns [5] brings focus on core technologies in enabling the design of very interactive and engaging dashboards to deliver rich insights from data. Data visualization frameworks such as D3.js and Chart.js work as cores that arm developers with the power to construct very interactive, aesthetically pleasing representations of very complex datasets. The research emphasizes the importance of web technologies. This basically includes such parts and layers as HTML, CSS, and JavaScripts in terms of responsive user-based interface designing. Conflated with this comes a sophisticated design on the user's front that effectively relates databases towards smooth integration in the latter.One of the very defining features of the modern dashboard systems is the application of the APIs, which allows the real-time updating of the current data. In this manner, as users engage with the applications, the dashboards tend to be dynamic and always responsive. This fusion of different technologies turns the dashboards into robust tools that can transform complicated datasets into intuitive and actionable insights for improving decision making and user engagement.

METHODOLOGY :

3.1 SMART Dashboard, sentimental analysis (LSTM/BD-LSTM)

Data Source: The study utilized the Open University Learning Analytics Dataset (OULAD), which includes demographic data, clickstream data (student interactions), and assessment scores.

The Key algorithms implemented include Long Short-Term Memory (LSTM) and Bidirectional LSTM (BD-LSTM) models, along with the BERT (Bidirectional Encoder Representations from Transformers) model for sentiment analysis on COVID-19-related Twitter data. These models are particularly effective in handling sequential data and understanding context, which is crucial for capturing the public's emotional and psychological state across different timeframes of the pandemic.

The LSTM and BD-LSTM models are designed to identify and analyze patterns in time series data, providing valuable insights into how sentiments shift over time with the rise and fall of COVID-19 cases, these models enable multi-label classification, allowing tweets to be labeled with multiple sentiments simultaneously (e.g., both "optimistic" and "joking").

Methods used in this paper involves Sentimental-analysis in real time for patient feedback, analyzing social media health trends, and interpreting public sentiments, The algorithm is specifically designed to process sequential data and capture the contextual dependencies that are essential for accurate sentimental classification in photos.

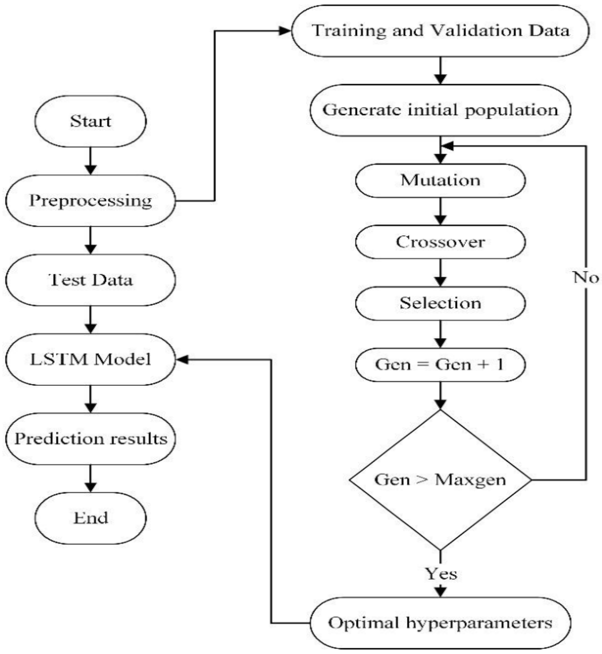


Fig. 1: LSTM working

3.2 Latent Dirichlet Allocation (LDA):

Latent Dirichlet Allocation (LDA) can then be applied to the geotagged health-related text for regional health patterns or issues. Here, social media posts, surveys, or other healthcare reports related to geographic metadata are collected. Then extraneous information in the text is removed and tokenized while preserving the spatial information for each document. Using LDA Latent Topics Then: Each latent topic corresponds to a group of related words, which in the health domain, may therefore correspond to the themes of "vaccine shortages," "disease outbreaks," or "discussions on mental health."

Once topics are identified, the preserved metadata links the topics to geographic locations and then presents the outcomes in maps or dashboards as a way of highlighting spatial distributions of specific health concerns. For instance, it might be a dashboard that points out regions with "high discussion about flu symptoms or COVID-19 vaccine access," enabling policymakers to pinpoint which areas needed attention right away. Such methodology aids in efficiently noticing and solving localized health issues.

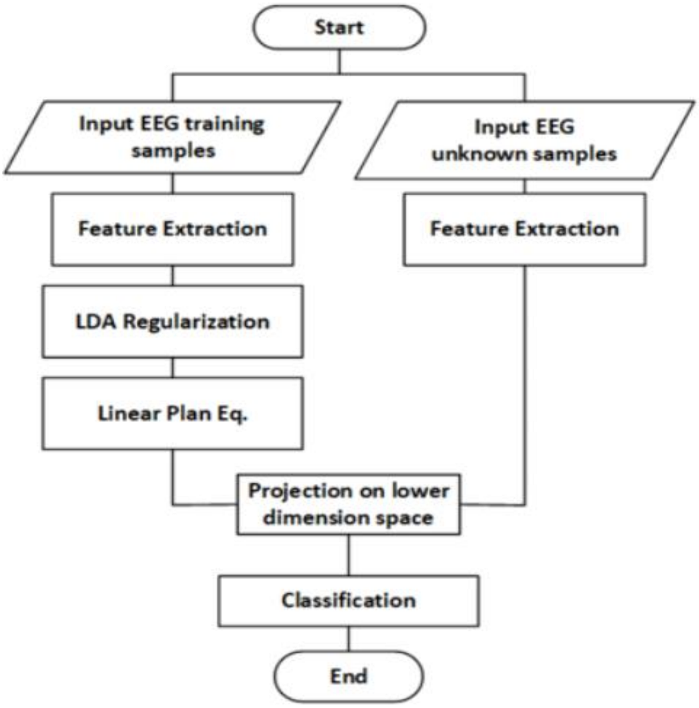


Fig. 2: LDA usage

3.2 YOLO v5:

This sophisticated object detection algorithm is incorporated into the methodology and finds its applications in real-time image analysis and pattern recognition. YOLOv5, specifically, finds special applications in processing medical images, monitoring facility conditions, and analyses of visual health data derived from social media or other sources.

It begins with the collection and processing of image datasets: X-ray or MRI scans, or facility inspection photos. These images are annotated to define the regions of interest: what medical conditions, malfunctions in equipment, or overcrowding in hospitals look like. With this annotated data, the training of YOLOv5 begins, which uses convolutional neural networks (CNNs) for object detection within a single pass to ensure speed and accuracy in analysis. The trained model would then be embeddable in the smart dashboard to analyse images in real-time that are incoming. In this case, the dashboard might identify certain patterns that indicate the spread of diseases in regions.

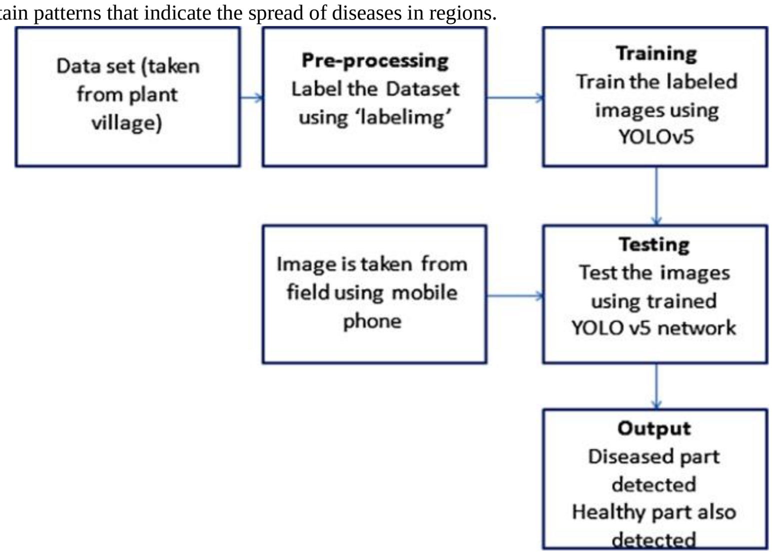


Fig. 3:Training an YOLO Model

Table 1: Comparison of YOLO with other models

Table 3. Performance comparison of SF-YOLOv5 and other algorithms on small object datasets.

Methods	Size	mAP@0.5	mAP@0.5:0.95	Parameters (M)	FLOPs (G)	Inference Time (ms)
YOLOv5s	640	69.7	35.5	7.01	15.8	13.1
YOLOv5-N5	640	69.9	35.3	1.88	11.2	10.4
YOLOv5-PB	640	70.8	36.0	2.03	12.7	11.3
SF-YOLOv5	640	71.3	36.3	2.23	13.8	12.2
improvement	-	+1.6	+0.8	−68.2%	−12.7%	−6.9%
YOLOv5n	640	63.9	30.8	1.76	4.20	8.60
SF-YOLOv5	640	71.3	36.3	2.23	13.8	12.2
improvement	-	+7.4	+5.5	+26.7%	+228.6%	+41.9%
YOLOv7-tiny	640	68.4	33.0	6.01	13.0	13.9
SF-YOLOv5	640	71.3	36.3	2.23	13.8	12.2
improvement	-	+2.9	+3.3	−62.9%	+6.2%	−12.2%
YOLOv3	640	74.5	39.5	61.5	154.7	44.7
SF-YOLOv5L	640	75.1	39.7	15.5	91.2	49.4
improvement	-	+0.6	+0.2	−74.8%	−41.0%	+10.5%
YOLOv7	640	76.1	39.5	36.5	103.2	18.0
SF-YOLOv5L	640	75.1	39.7	15.5	91.2	49.4
improvement	-	−1.0	+0.2	−57.5%	−11.6%	+174.4%
ResNeXt-CSP	640	73.7	37.6	31.8	58.9	32.6
SF-YOLOv5L	640	75.1	39.7	15.5	91.2	49.4
improvement	-	+1.4	+2.1	−51.3%	+54.8%	+51.5%

3.2 VGG-16:

For incorporating **VGG-16** into a smart healthcare dashboard, the methodology involves leveraging its deep convolutional neural network (CNN) architecture for image classification and feature extraction. VGG-16, known for its simplicity and accuracy, is particularly suited for analyzing medical imaging data and visual content related to healthcare.

The process begins with the collection of healthcare-related image datasets, such as X-rays, CT scans, or photographic records from hospitals. These images are pre-processed, including resizing to match VGG-16's input requirements (typically 224x224 pixels) and normalizing pixel values. The VGG-16 model, pretrained on ImageNet, can then be fine-tuned or retrained on the specific healthcare dataset to adapt it to the required task.

Once trained, VGG-16 can be integrated into the dashboard to perform tasks such as detecting abnormalities in medical images, classifying disease types, or monitoring hospital environments. For instance, it can assist in identifying patterns in X-rays indicative of pneumonia or in categorizing skin lesions for early diagnosis of melanoma. Its 16-layer architecture ensures robust feature extraction, making it reliable for handling complex medical imaging data.

The processed results, such as classifications or highlighted abnormalities, are visualized on the dashboard. Heatmaps or annotated images can provide detailed insights for healthcare professionals, enabling quick and informed decision-making. Integrating VGG-16 into a healthcare dashboard enhances its analytical capabilities, promoting efficiency and accuracy in medical diagnostics and healthcare management.

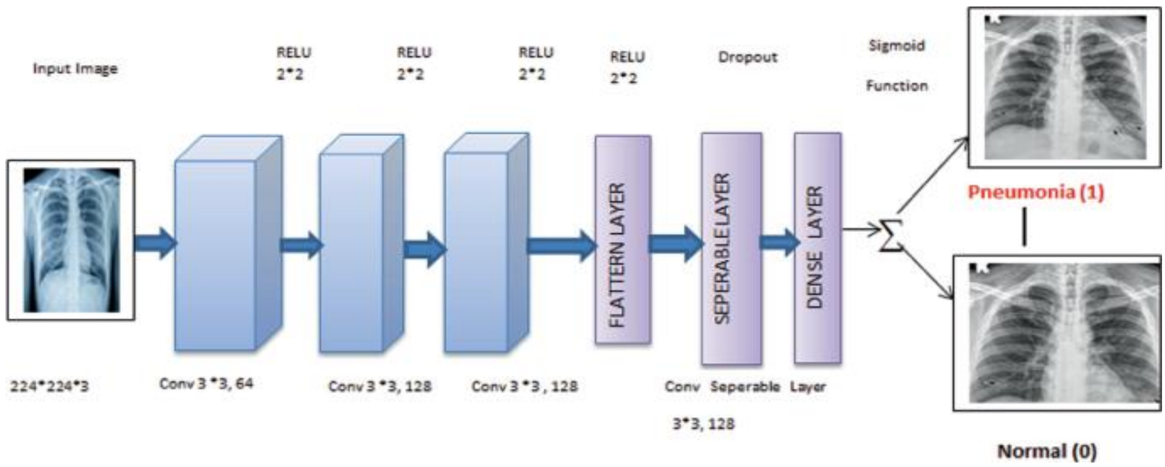


Fig. 4. Analysis of a MRI picture uploaded in X(Twitter)

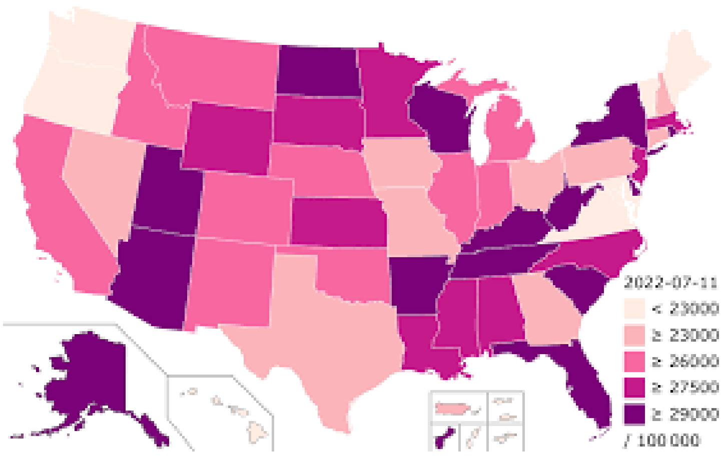


Fig. 5. Understanding Patterns

3.2 *chart.js, D3.js, Frameworks:*

Technologies involved in this methodology include visualization libraries such as **D3.js** and **Chart.js** for dynamic visual elements, frontend frameworks like **React** and **Angular** for user interface development, and data processing tools such as Node.js for real-time data integration. Additionally, user experience tools like Figma were utilized for prototyping.

Chart.js is a straightforward, lightweight library perfect for displaying simple visualizations such as bar charts, line graphs, and pie charts. It integrates easily with x API by receiving data in JSON format, such as healthcare metrics or trends, and then visualizing that information in a clear and responsive manner. This makes it ideal for tracking policy effectiveness, like vaccine distribution over time or patient satisfaction across regions. On the other hand, **D3.js** is a more advanced, customizable tool that allows for the creation of complex visualizations such as heatmaps, geographic maps, or network graphs. D3.js can take data from x API and transform it into dynamic, interactive visuals that can help policymakers understand spatial distributions or multi-dimensional relationships, such as the impact of health policies on different demographic groups.

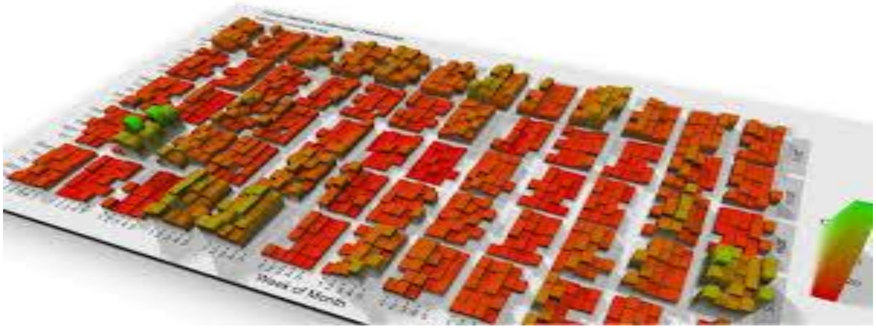


Fig. 6. 3D heatmap of a location

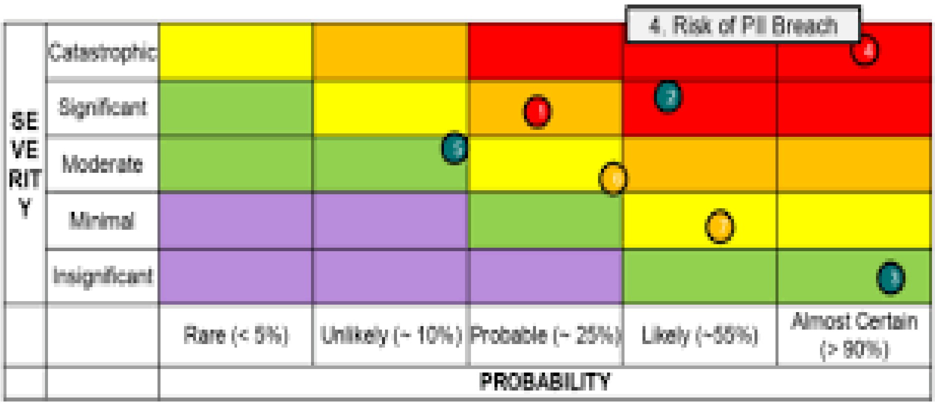


Fig. 7. How catastrophe is classified using colors

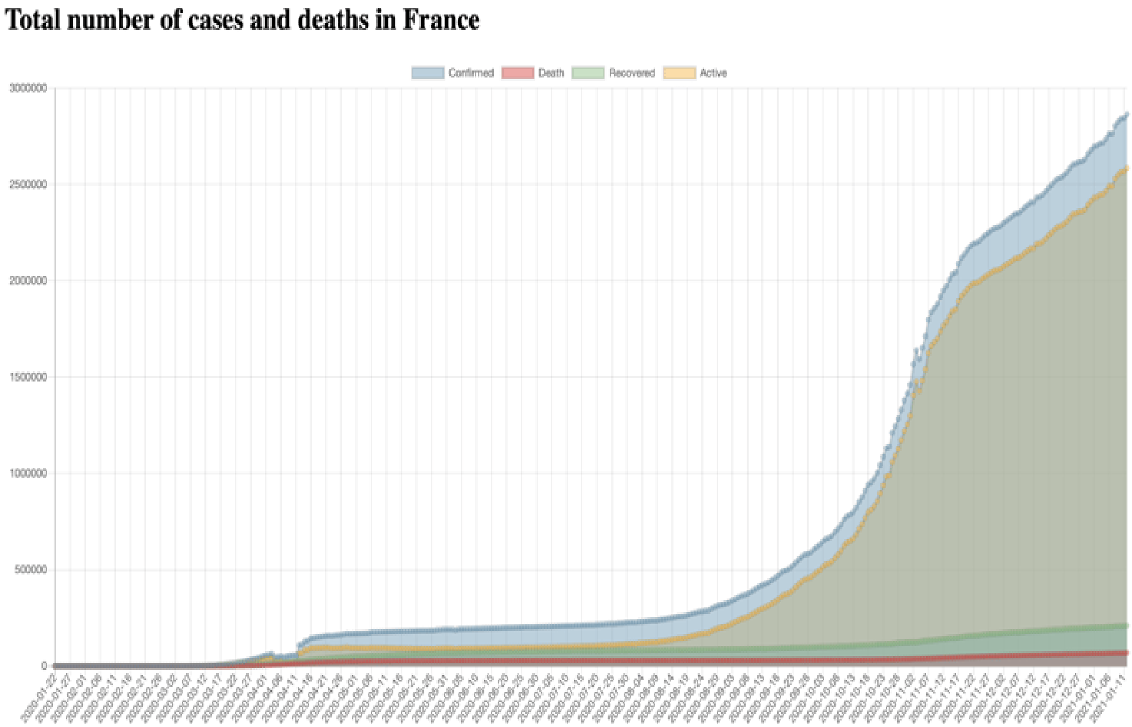


Fig. 8. Deaths of a catastrophe using chart.

RESULTS and DISCUSSION:

In this Paper, I want to present a SMART dashboard which is totally related to epidemic and pandemic diseases by using Retweets from X(Ex-Twitter) and Threads from Instagram, This method helps the policy makers to think about the precautions to take before spreading of any virus

4.1 *Data-set:*

- Collecting the Retweets from the platforms like Twitter, Threads using Hashtags (Ex- #COVID19, #Influenza)
- Track the number of retweets to see how quickly information spreads
- Analysis of emotions should be considered either(positive, negative) to understand public point of view
- Usage of Geo-Tagged tweets to identify the regions to know the outbreak of virus and its vast spreading
- We should also focus on Influential public figures i.e. Ministry of Health and other governing bodies to know the exact details of a virus

4.2 Feature selection:

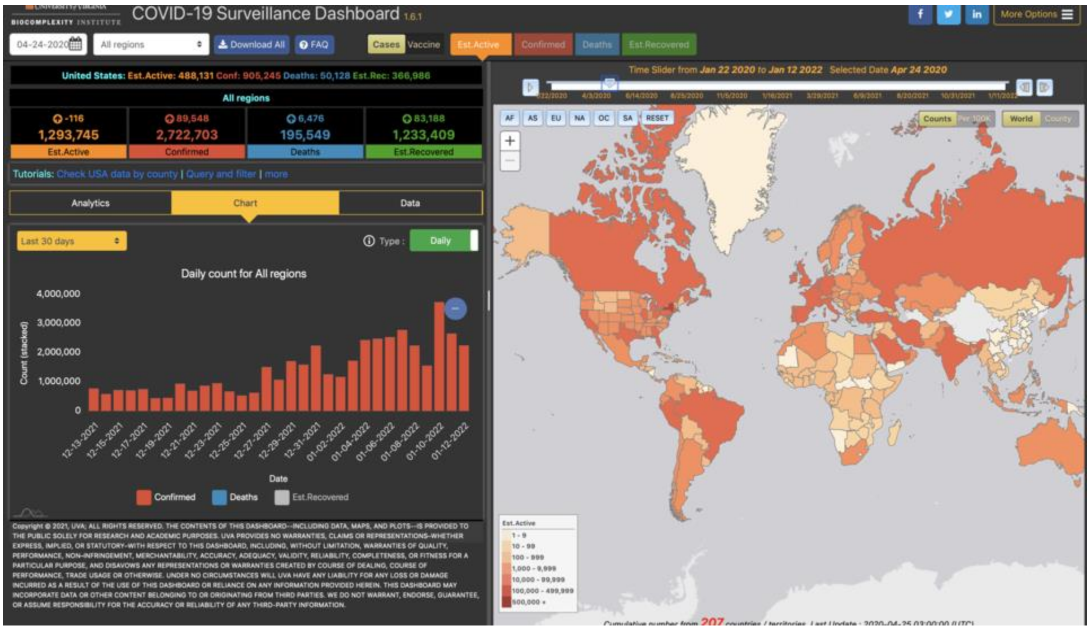
The following features are taken from the dataset as follows:

Features	Definition
Hashtags	To know the trend
Keywords	analyze virus-specific terms (symptoms)
Retweet Count	Track how many times it has been retweeted
Quote Tweets	Quoted tweets for deeper insights
Verified Status	Tweet from these account tells credibility
Follower Count	Indicates the influence of the user
Retweet Growth Over Time	To track virality trends
Location Tags	To identify hotspots of virus
Emotion Detection	To identify emotions in tweets to know the response
Topic Modeling	LDA (Latent Dirichlet Allocation) to extract themes

4.3 IMPLEMENTATION:

To implement a comprehensive COVID-19 dashboard using data analytics, you first need to collect real-time data from Twitter through the Twitter API, focusing on virus-related tweets, retweets, and threads. After collecting the raw data, preprocessing steps like cleaning the text (removing URLs, special characters, and retweet artifacts), tokenizing, and normalizing engagement metrics (e.g., retweet and like counts) are necessary. Geolocation data from tweets helps map virus-related discussions to specific regions. Once the data is clean, sentiment analysis and emotion detection can be applied to measure public reactions toward the pandemic, which helps in identifying public concerns and misinformation. Time-series analysis can be performed by aggregating retweet counts and tweet frequencies over different time intervals to detect spikes in virus-related conversations. Topic modeling using techniques like Latent Dirichlet Allocation (LDA) or non-negative matrix factorization (NMF) can identify key topics and themes in Twitter discussions, such as vaccines, lockdowns, or emerging symptoms. Machine learning algorithms like Random Forest or Gradient Boosting can be used to predict the spread of information, while Logistic Regression or Support Vector Machines (SVM) can classify tweets based on sentiment. Additionally, Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), can be employed for trend forecasting to predict future public discussions about the pandemic. The dashboard should also integrate visualizations to display trends in public sentiment, retweet patterns, and geospatial data, helping policymakers understand public perception and potential outbreaks. Additionally, for backend API calls and requests we add Django or Flask, and for database storage we use MangoDB because it can handle unstructured twitter data in real-time, and finally for the security purposes we use OAuth2.0 for secure authentication.

Fig. 9.Dashboard with spatio-temporal analysis



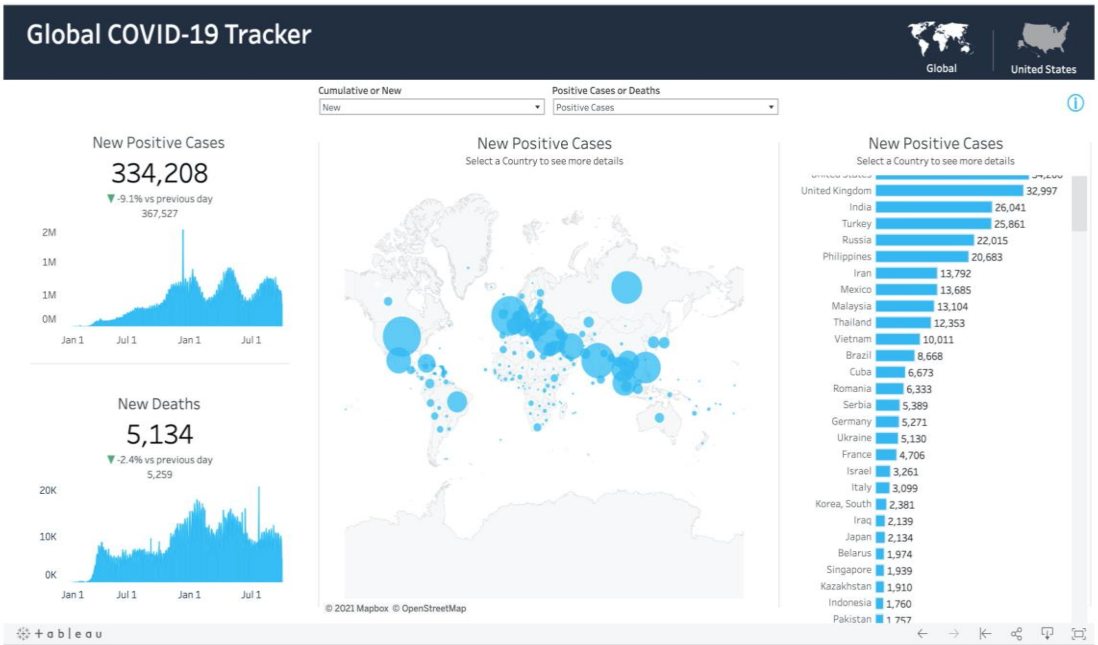


Fig. 10. Realtime data Monitoring on live scale

Conclusion :

In conclusion, The SMART dashboard is a pioneering tool especially designed for use by policymakers, in and of itself a big leap into the world of public health surveillance and preventive measures before epidemics and pandemics might break out. Advanced technologies incorporating real-time data assessment, machine learning algorithms, and rigorous social media monitoring, among others, allow it to detect even slighter warnings of potential health-related emergencies. This predictive method detects subtler and diverse patterns related to health that are perhaps not noticeable with other traditional approaches.The sophistication of methodologies such as sentiment analysis, geospatial data processing, and epidemic forecasting allow the dashboard to derive actionable insights from vast and diverse datasets. This functionality plays a critical role in providing policymakers with the necessary tools to optimize resource allocation, deliver timely health advisories, and execute targeted interventions. With the taking of preemptive action, decision-makers can alleviate the intensification of a health crisis and guarantee that resources are distributed effectively, thereby preventing the onset of widespread panic and overall diminution of impact. This improves the richness and reliability of the dashboard, and evidence-based decision-making is strengthened through its capability of forecasting. It not only solves emerging crises but also forces health care systems to engage in promoting resilience in healthcare. As the public health impact of a new disease is relieved from the reactive approaches now focusing on proactive strategies, this enhances the capability of the health system to meet the expected challenges. In this sense, the SMART dashboard constitutes a new paradigm for public health governance-a paradigm through which policy can anticipate, prepare for, and respond to potential health crises in novel ways. This is an example of how technology can be used to create a more responsive and adaptive system in which public health crises are prevented before they have a chance to occur, thus creating healthier and safer societies.

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