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Automated Multidimensional Analysis of Global Events With Entity Detection, Sentiment Analysis and Anomaly Detection

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ABSTRACT The modern era, with information overload, has compelled strategic decision makers to obtain assistance from artificial intelligence- (AI) based decision support systems (DSS). Data-driven DSSs powered by powerful AI algorithms can instantly categorize unstructured data, assign context, and produce meaningful insights from such data. This paper presents an automated media monitoring system that can analyze unstructured global events reported in online news, government websites, and major social media to produce significant insights with explainable AI. Using this innovative system, a decision maker can focus on global events requiring urgent attentions since it segregates millions of unnecessary data by using the presented methodology involving entity detection, sentiment analysis, and anomaly detection. The system was designed, deployed, and tested during June 2, 2021 – September 1, 2021. During this 92-day period, the system connected to 2,397 distinct types of news sources and automatically fetched 22,425 major event descriptions from 192 countries. Then, to assign meaning and context to the unstructured event descriptions, the system performed AI-based entity detection and sentiment analysis of these global events. The proposed system is sufficiently robust to detect anomalies instantly from 2.76×10^{8404} possible scenarios and provides detailed explanations by using natural language descriptions along with dynamic line charts and bar charts to portray detailed reasoning. The entity detection algorithm had a F1-score of 0.994 and the anomaly detection algorithm had an area under curve score of 0.941, establishing the proposed system with explainable AI as the most accurate, robust media monitoring system according to the literature.

INDEX TERMS Anomaly detection, decision support system, entity detection, media monitoring with explainable AI, sentiment analysis.

I. INTRODUCTION

With the advent of online news portals, e-governance and social media, millions of global events are generated on a regular basis [1]. The manual monitoring and analysis of millions of global events are becoming a challenging task. Hence, there has been a surge of research on automated sentiment analysis and entity detection [2]–[12]. However, the effectiveness of these systems is limited by the machine's current inability to explain the decisions and actions of these systems to users. Explainable artificial intelligence (AI) is essential for human users of AI systems to understand, trust appropriately, and adopt effectively the advice generated by AI. Therefore, in recent times, industry giants, such as Google, IBM and Microsoft, have devoted increased effort to implementing explainable AI [13]–[15].

In this study, we propose a methodology through which we harness the current advancement of AI services and algorithms to design, develop, and implement a fully automated media monitoring solution that analyses global events automatically, highlights significant events to users and explains the root causes of abnormalities in plain English language. As Fig. 1 illustrates, event descriptions could originate from any social media (e.g., Twitter, Facebook, and Instagram), online newspapers, and the government websites of any country. These event descriptions typically have a message-ID, a media source (e.g., the link to the news site), and the time of initiation. By using the entity detection and sentiment analysis process described in this paper, multiple dimensions of feature attributes (e.g., location, group, district,

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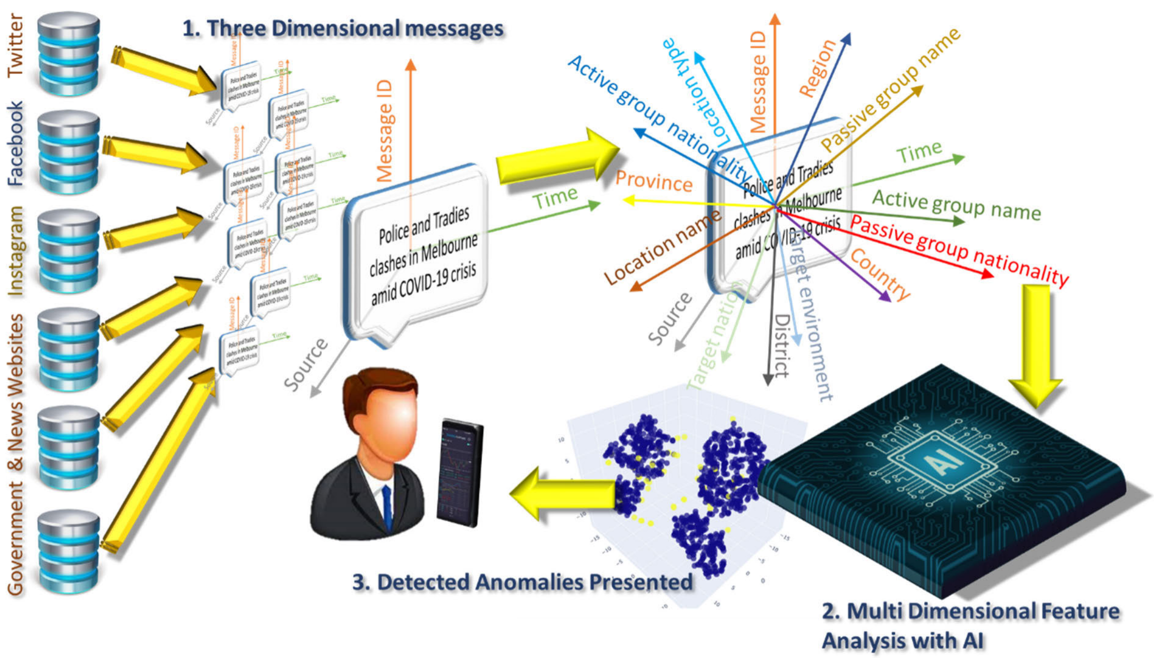

FIGURE 1. **Overview of multidimensional media message analysis and anomaly detection.**

country, region, and the nationality of the person conducting the event) are created from the original three-dimensional news. Hence, AI-based anomaly detection can automatically detect all the abnormal events and discover the root causes of these anomalies by analyzing all the feature attributes. Last, the results are presented to the user through a mobile app, a tablet or a desktop computer in natural language using natural language processing (NLP) [16]. Typical users of the proposed system would be geopolitical decision makers, diplomats, and leaders who want to be aware of any major global event as it occurs. Moreover, local news agencies covering international news could also be users of such a system.

The proposed system was deployed and evaluated for monitoring global events from June 2, 2021 to September 1, 2021. During this period, the automated system collected 22,425 global events, created context and meaning for these events, and highlighted any possible abnormality by using explainable AI. Hence, system users would immediately know which events are more important than others and why they are important in plain language.

First, the Background section provides necessary brief of the existing body of knowledge based on which we designed the proposed methodology. Next, Material & Methods section provides a conceptual understanding of the core modules utilized in this study. These core modules include a media aggregation engine, entity detection, sentiment analysis and anomaly detection algorithm with spectral residual (SR) with a convolutional neural network (CNN). Since the Material & Methods section only provides the conceptual and theoretical background, the next section, Calculation, provides implementational details of the proposed methodology. The Calculation section provides the deployment architecture, which demonstrates the implementational details in actualizing the proposed methodology with seamless integration.

Next, the *Results* section shows that the proposed system was deployed and monitored for 92 days and that within this timeframe, the automated system successfully gathered 22,425 descriptions of global events from 2,397 news sources, including social media. Our results also show that the system was able to automatically categorize 27,827 entities from the global event descriptions into 12 different entity types (e.g., who conducted the event, what is their nationality, where did the event take place, and who was the target). Moreover, our system automatically extracted the sentiments of these events and assigned the sentiments to the detected entities. Therefore, a user can easily obtain insightful answers to queries such as "what is the most significant event on a particular day" and "what was the location of most destructive event yesterday." The proposed system successfully highlighted abnormal activities and explained the reasoning using both text and visualization. Hence, explainable AI was successfully demonstrated within the *Results* section.

Then, in the *Discussion* section, the end-to-end evaluation of the robustness and accuracy of the proposed system is presented. This section explains how the system could identify abnormal events through our implementation of an anomaly detection algorithm, from a vast range of 2.76×10^{8404} possible scenarios. The area under curve (AUC) score, which indicates the overall accuracy of the anomaly detection algorithm, was 0.941. The entity detection had an overall classification accuracy of 0.994, as shown by the F1-score.

According to the findings reported in the literature and to the best of our knowledge, the proposed system provides the highest quality of robustness along with a high level of accuracy, for detecting abnormal global events with seamless integration and explainable AI.

II. BACKGROUND

A literature review on global news sentiment shows that the overall sentiments in global news published by news agencies are gradually becoming more negative [17], [18]. This change has been occurring mainly because the public is more attracted to negative news and media agencies are hence merely meeting their consumers' demand for more negative news [19]. A deep analysis of global media through sentiment analysis is extremely important since it can reveal the gradual changes in the tone of negativity toward a foreign entity, a group, or a location [17]. More importantly, by analyzing the gradual change in event sentiments, it is also possible to predict likely events [17].

Nevertheless, despite the importance of conducting an in-depth analysis of the sentiments toward global events, most of the mainstream literature has obtained their media message only from one or two media sources, as Table 1 shows.

These studies mainly depended on a single source of information, such as Twitter [9], [10], [20], [21], Facebook [22], Instagram [23], Amazon reviews [24], and online blogs [6], [25], for conducting sentiment analysis research. Very few sources also used website portals of online news agencies such as BBC, New York Times, and Summary of World Broadcast [17], [26], [27]. In a more recent work, the researchers aggregated protest events from 30 countries from 10 news sources with the expense of time-consuming manual coding [28].

Other than a few studies like [3] and [6], most did not utilize entity detection methods or named entity detection for performing a multidimensional analysis. In the next sections, we will delve more into the details of existing research on sentiment analysis, entity detection, and anomaly detection.

III. MATERIAL & METHODS

To perform an automated analysis of global event, the desired system would require a media aggregation engine. Then, to generate the context and semantics of unstructured event descriptions, the aggregated events would have to be analyzed by using entity detection and sentiment analysis. Entity detection and sentiment analysis would generate features and attributes that could be further analyzed by using AI algorithms with explainable AI. Fig. 2 depicts the schematic of the proposed methodology.

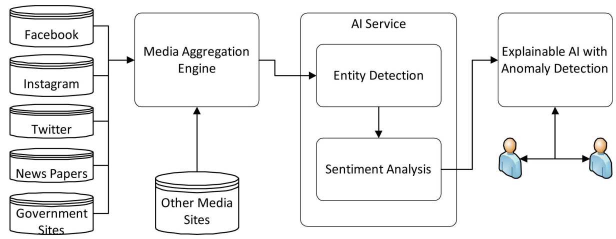

FIGURE 2. Schematic diagram of explainable AI with AI services and anomaly detection algorithm.

A. MEDIA AGGREGATION

The media aggregation engine collects and stores the global media data from several sources by covering all major social media (e.g., Twitter, Facebook, Instagram, and YouTube), government websites (i.e., police websites, defense media websites, and foreign affairs websites), and the websites of national news agencies and of national and international TV/Radio channels, among others. Our media aggregation engine allows us to connect and automatically receive event updates from a wide range of online media through dedicated application programming interfaces (APIs) and web scraping technologies to collate new events or event updates into our global event database. Once all the online media sites are connected, the task of event collection into the database becomes completely automatic, until the source media sites change their websites or APIs. The media aggregation module of our system, only captures and retains descriptions (500-character text) of new or updated events.

Previously, we reported on AI and Machine Learning (ML) algorithms for solving multi-disciplinary problems, ranging from abnormality detection [29]–[31] to person identification [32] and knowledge discovery on landslides [33], and all these previous studies required feature attributes to be present on which the ML algorithms could operate. Therefore, for this study, more feature attributes must be generated from the event description. Entity detection extracts feature attributes from event description (which was captured by the media aggregation module).

B. ENTITY DETECTION

Entity detection is an information extraction task that seeks to locate and classify named entities mentioned in unstructured text into predefined categories, such as person names, organizations, locations, medical codes, time expressions, quantities, monetary values, and percentages. Entity detection has been used in almost all domains to extract key information from unstructured text [2], [3].

Previous research has extracted three types of entities (i.e., "Disease or Syndrome," "Sign or Symptom," and "Pharmacologic Substance") from health-related tweets [2] for discovering public health information and developing real-time prediction systems with respect to disease outbreak prediction and drug interactions.

In [3], basic NLP approaches were used to extract entities and relationships, and to identify sentiment. The keywords searched within [3] were *Drug Abuse—Cannabinoids*, *Buprenorphine*, *Opioids*, *Sedatives,* and *Stimulants*.

TABLE 1. Studies on sentiment analysis and Entity detection with media sources and algorithm used.

Reference	Media source used	Year	Entity detection used?	Algorithm & methodology used
[26]	BBC News Database	2017	No	Word comparison with Bing Liu dictionary
[27]	COAE2014 (BBC DataSet)	2017	No	Language Technology Platform (LTP) for dependency syntax analysis
[20]	Reviews of electronic products from Twitter	2018	No	Valence Aware Dictionary and Sentiment Reasoner (VADER)
[24]	Amazon Customer Review Data	2018	No	Naive Bayes, support vector machine
[25]	Hotel reviews from OpinRank	2018	No	Naive Bayes
[22]	Facebook	2018	No	Support vector machine, K-nearest neighbor, decision tree
[23]	Instagram	2018	No	Elastic-net regularized linear regression model
[3]	Social media (unspecified)	2013	Yes	Entity detection was used to detect 3 different entities and to identify sentiments on them
[6]	French patient forum	2018	Yes	Entity recognition, topic modeling, sentiment
[21]	Twitter	2017	No	AutoML with best results from support vector machine with term frequency-inverse document frequency (TF-IDF)
[9]	Twitter	2019	No	Deep feature ensemble
[10]	Twitter	2021	No	Support vector machine
[17]	Summary of World Broadcast; New York Times	2011	No	Sentiment mining and full–text geocoding

Further, in [6], a qualitative analysis was conducted of posts about *methylphenidate* from five French patient web-forums, including an analysis of information about misuse or abuse. Data were collected from French social networks that mentioned methylphenidate keywords. Text mining methods, such as named entity recognition and topic modeling, were used to analyze the chatter, including the identification of adverse reactions.

In this study, we used entity extraction to extract 12 different entity types from global event descriptions. These entities are region, country, district, province, location name, location type, active group name, active group nationality, passive group name, passive group nationality, target environment, and target nation. Subsequently, these entities have become the feature attribute of the anomaly detection algorithm.

C. SENTIMENT ANALYSIS

Research on the sentiment analysis of English text started in 2002 with the publication of two studies: [11] and [12]. The study in [11] presented a supervised learning corpus-based machine classifier and that in [12] presented an unsupervised classifier based on linguistic analysis. Earlier, sentiment analysis was mostly focused on product and movie reviews. It expanded to other domains after the emergence of social media websites. Several studies followed, such as [4]–[12]. Recent systematic reviews on sentiment analysis are available in [34].

Sentiment analysis has been used to assess customer feedback for understanding the political sentiments of people, specifically to predict election results [21]. Studies have collected location-based political messages on the Citizenship Amendment Act from Twitter. However, the tweet locations were extracted using the location field of the tweeters [10]. The main drawback of using this field is that people tend to move around, and tweets can retain an old, invalid user address. Moreover, if users have not enabled location services, the analysis of tweet messages could yield flawed results. Recent research has demonstrated that fusing the location feature with the sentiment analysis process improves tweet sentiment classification [35].

Since sentiments are determined for event descriptions, and entity detection extracts entities from event descriptions, in this study, the sentiments associated with an event description are applied to all the entities extracted from that same event description.

D. ANOMALY DETECTION

The anomaly detector enhances line charts by automatically detecting anomalies within time-series data. It also provides explanations for the anomalies to facilitate root-cause analysis. In our most recent study, we have harnessed the anomaly detection algorithm to identify abnormal cases of landslides and obtain the root causes of these anomalies [33]. Before delving into the details of anomaly detection, we present the problem definition.

Problem 1: Given a sequence of real values, that is, $x = x_1, x_2, x_3, \ldots, x_n$, the task of time-series anomaly detection is to produce an output sequence $y = y_1, y_2, y, \ldots, y_n$, where $y_i \in \{0, 1\}$ denotes whether x_i is an anomaly point.

The implemented solution borrowed the SR from the visual saliency detection domain and then applied a CNN to the results produced by the SR model [36].

The SR algorithm consists of three major steps:

1) Perform Fourier transform to obtain the log amplitude spectrum.
2) Calculate the SR.
3) Perform inverse Fourier transform, which transforms the sequence back to the spatial domain.

$$A(f) = Amplitude(f(x)) \tag{1}$$

$$P(f) = Phrase(f(x)) \tag{2}$$

$$L(f) = log(A(f)) \tag{3}$$

$$AL(f) = h_q(f).L(f) \tag{4}$$

$$R(f) = L(f) - AL(f) \tag{5}$$

$$S(x) = \left\| f^{-1}(\exp(R(f) + iP(f))) \right\| \tag{6}$$

where f and f^1 denote the Fourier transform and inverse Fourier transform, respectively; x is the input sequence with shape $nX1$; $A(f)$ is the amplitude spectrum of sequence $\boldsymbol{x}$; $P(f)$ is the corresponding phase spectrum of sequence x; $L(f)$ is the log representation of $A(f)$; and $AL(f)$ is the average spectrum of $L(f)$, which can be approximated by convoluting the input sequence by $h_q(f)$, where $h_q(f)$ is a $q \times q$ matrix defined as:

$$h_q(f) = \frac{1}{q^2}\begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \dots & \vdots & \ddots & 1 \\ 1 & 1 & \dots & 1 \end{bmatrix} \tag{7}$$

$R(f)$ is the SR, that is, the log spectrum $L(f)$ minus the averaged log spectrum $AL(f)$. The SR serves as a compressed representation of the sequence, whereas the innovation part of the original sequence becomes more significant. Last, the sequence was transferred back to the spatial domain using an inverse Fourier transform. The resultant sequence $S(\boldsymbol{x})$ is referred to as the saliency map [37]. The values of the anomaly points are calculated as follows:

$$x = (\overline{x} + mean)(1 + var).r + x \tag{8}$$

where $\overline{x}$ is the local average of the preceding points, *mean* and *var* are the mean and variance of all points within the current sliding window, and $r \sim N(0, 1)$ is randomly sampled. In this process, CNN is applied to the saliency map instead of to the raw input, thus increasing the efficiency of the overall process of anomaly detection [36], [37].

The anomaly detection algorithm provides detailed explanations for all detected anomalies following the root-cause analysis performed by the AI services. In fact, we implement anomaly detection in three steps:

1) Detect all the anomalies within the time series (i.e., any values that lie outside the threshold range).
2) Identify the main drivers of these anomalies.
3) Explain the results in a natural language (explanation of the root cause) using NLP [16].

As shown in Fig. 3, a particular event is highlighted as an anomaly. The description of the event informs "*Police and Tradies clashes in Melbourne amid COVID-19 crisis*". The negative sentiment associated with this news resided outside the sentiment threshold and it was hence classified as an anomaly. The entity detection process analyzed this news and revealed "Melbourne" as the *location* of the incident, "Police" as the *active group name*, and "Tradies" as the *passive group name*. The root-cause analysis by the anomaly detection algorithm further revealed that within a similar set of news, the *location* name and the *active group name* had been the prime drivers for news with higher negativity specifically when the *location* was Melbourne and the *active group name* was Police. Last, using NLP, the result is presented to users in plain English.

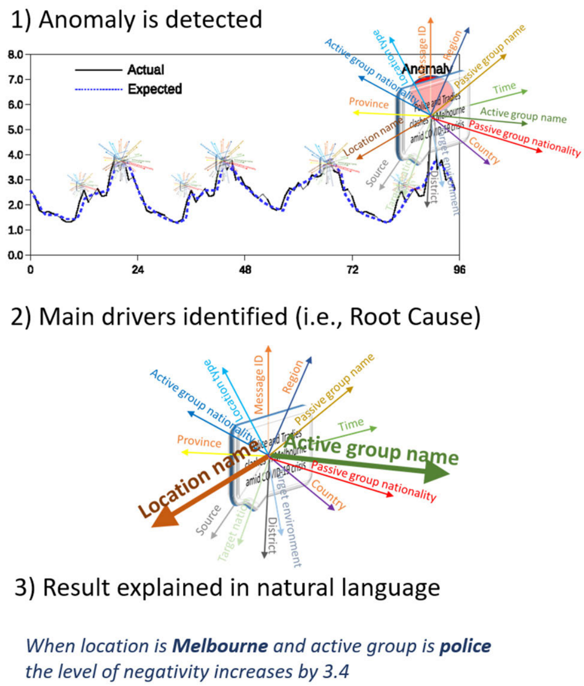

FIGURE 3. Step-by-step activities performed in our implementation of anomaly detection.

IV. ALGORITHM & IMPLEMENTATION

The media aggregator module creates a set of event descriptions D, as follows: $D = \{d_1, d_2, d_3, \dots, d_n\}$.

The *Entity_detection()* function takes event descriptions and creates a list of entities for that event description, as shown in (9).

$$Entity\_Detection(d_n) = \{e_1^n, e_2^n e_3^n, \dots, e_m^n\} \tag{9}$$

In this study, we used sentiment analysis on the event description. The *Sentiment_Detection()* function takes the description of the event and provides three different scores: positive sentiment confidence s_{Pos}^n, negative sentiment confidence s_{Neg}^n, and neutral sentiment confidence s_{Neu}^n. Each of these three sentiment scores can take any decimal values between 0 and 1. This is shown in (10).

$$Sentiment\_Detection(d_n) = \{s_{Pos}^n, s_{Neg}^n, s_{Neu}^n\} \tag{10}$$

The overall sentiment s_n for an even description d_n is a text value of either *Positive*, *Negative*, *Neutral*, or *Mixed*, as determined by Eq (11).

$$s_n = \begin{cases} Positive, & If\ s_{Pos}^n > 0.65 \\ Negative, & If\ s_{Neg}^n > 0.65 \\ Neutral, & If\ s_{Neu}^n > 0.65 \\ Mixed, & If\,(s_{Pos}^n \le 0.65) \\ & \bigwedge(s_{Neg}^n \le 0.65) \bigwedge (s_{Neu}^n \le 0.65) \end{cases} \tag{11}$$

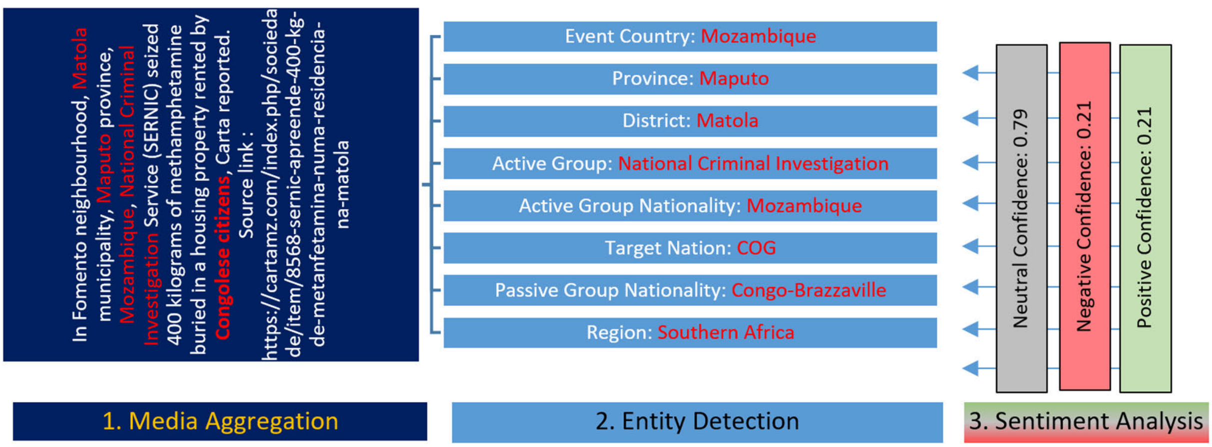

FIGURE 4. An example of generating entities and sentiments from event description.

Once the sentiment is obtained for an event description, all the extracted entities for that event description inherit the same sentiment. For example, if the neutral sentiment score of an event is found to be 0.79, then all the entities belonging to that particular event would also have a neutral sentiment score of 0.79.

This can be observed from Fig. 4, which shows that an event description was fed through *Entity_Detection()* and eight entities were extracted (i.e., Event Country, Province, District, Active Group, Active Group Nationality, Target Nation, Passive Group Nationality, and Region. The sentiment associated with this event is applicable to all these extracted entities. Hence, from the example shown in Fig. 4, *Mozambique* country would inherit a neutral sentiment of 0.79, because the event description for the presented example in Fig. 4 has a neutral sentiment confidence of 0.79. Next, if we wanted to obtain the overall sentiment about Mozambique, we would aggregate all the sentiment scores obtained on the country entity Mozambique from all the event descriptions collected by the media aggregation module. Hence, the aggregated sentiment of entity E_m is defined as $S_{E_m}^{Pos}$ for the aggregated positive sentiment for entity E_m, $S_{E_m}^{Neu}$ for the aggregated neutral sentiment for entity E_m, and $S_{E_m}^{Neg}$ for the aggregated negative sentiment for entity E_m.

Equations (12), (13), and (15) define this concept of aggregated sentiment on an entity.

$$S_{E_m}^{Neg} = \sum_{n=1}^{N} s_{Neg}^{n} \tag{12}$$

$$S_{E_m}^{Pos} = \sum_{n=1}^{N} s_{Pos}^{n} \tag{13}$$

$$S_{E_m}^{Neu} = \sum_{n=1}^{N} s_{Neu}^{n} \tag{14}$$

Algorithm 1 shows the implementation of the methodology described in this paper.

Algorithm 1 Create Entity-Centric Sentiments for Global Event Feeds

Input: *Incoming Media Message,* $D = \{d_1, d_2, d_3, \ldots, d_n\}$
Output: *Anomalies* A_j *and corresponding root causes* V_p
//Detect all the entities present within the messages and categorize them under entity categories
For Each $d_n \in D$, *n=1 to* $|D|$
  $e_m^n \leftarrow NamedEntity(Detect\_Entities(d_n))$
  $c_k \leftarrow EntityCategory(Detect\_Entities(d_n))$
  If $e_m^n \in c_k$ Then
    $c_k \leftarrow e_m^n$
  End If
Loop
For each e_m^n where $m = 0$ to M and $n = 0$ to N
  If $e_m^n \notin \mathbf{E}$
    $\mathbf{E} \leftarrow e_m^n$
    $S_{E_l} \leftarrow Sentiment\_Detection(d_n)$
  Else
    $S_{E_l} \leftarrow S_{E_l} + Sentiment\_Detection(d_n)$
End if
Loop
//Anomaly detection detects the anomaly A_j *and corresponding root causes* V_p
$\{A_j, \{V_p\}\} \leftarrow AnomalyDetection(c_k, E_l, S_{E_l})$

These aggregated sentiments on all the entities could be applied at the top level (i.e., region) and could be drilled down to the selected province, district, locations, or event for the selected date range. Hence, the methodology described above provides a unique perspective on the locations and the actors (i.e., which organization conducted the activity) with detailed sentiments. When the anomaly detection algorithm is

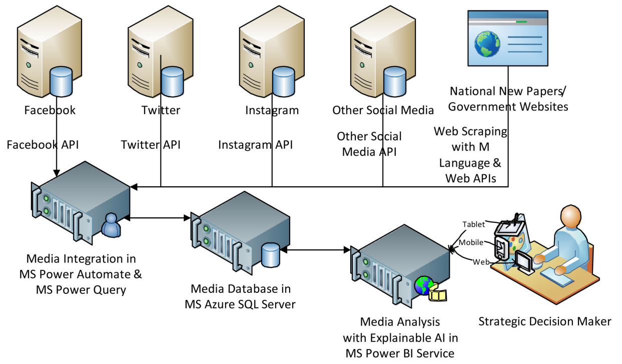

FIGURE 5. High level architectural diagram of the proposed location-oriented sentiment analysis solution on global events.

TABLE 2. Total entities successfully categorized under 12 different entity types with entity detection.

Entity Type	Number
Region (E1)	18
Country (E2)	192
District(E3)	3655
Province (E4)	2324
Location Name (E5)	11668
Location Quality (E6)	9
Active Group Name (E7)	4322
Active Group Nationality (E8)	257
Passive Group Name (E9)	4395
Passive Group Nationality (E10)	540
Target Environment (E11)	5
Target Nation (E12)	442
Total	27,827

applied on the aggregated sentiment (either negative, positive, or neutral) over time, the algorithm detects all the anomalies and explains the anomalies with respect to all the attribute features obtained though entity detection. All the AI services and algorithms described above were implemented using Microsoft Cognitive service (e.g., *Entity_Detection()* and *Sentiment_Detection()*), Microsoft ML.Net, and the associated Microsoft ecosystem, including MS Power Automate, MS Power BI, and MS Azure SQL [38], [39]. Since a typical decision maker requires the information to be presented on a wide range of devices to support instant decision-making, the deployed solution has been made accessible on a range of devices, including web, tablet, and mobile platforms. As shown in Fig. 5, Microsoft Power Automate along with ML .Net and various APIs were used to implement explainable AI.

First, social media APIs and the proposed solution can be used to integrate social media feeds by using the cloud-based MS Power Automate integration tool. As shown in Fig. 5, the system is also capable of integrating real-time website feeds or online forum feeds using web scraping with M Language within Microsoft Power Platform. Social media data with sentiments, translations, and entities were maintained within MS Azure SQL Server. The MS Power BI service is connected to MS Azure SQL Server for presenting the dynamic explainable AI content to the strategic decision maker through mobile, tablet or web interfaces.

FIGURE 6. Sentiment analysis of 22,425 events on the respective country.

V. RESULTS

We monitored and aggregated news items on global media from June 2, 2021 to September 1, 2021 by using our media aggregation module. The news aggregation module connected with 2,397 distinct types of news sources, including national news agencies (of 192 countries), government websites, Twitter, Facebook, Instagram, and YouTube. We collected exactly 22,425 individual news items in our database during the monitored period. We analyzed these 22,425 media articles through the entity detection process. Table 2 shows entities that were detected.

After the entity detection process, the sentiment analysis process was performed on the news descriptions, which returned four values for each of the 22,425 media descriptions: the overall segment of the description (i.e., string text denoting *positive*, *negative*, *neutral*, or *mixed*), the confidence percentage of positivity (double-precision decimal number from 0 to 1), the confidence percentage of negativity (double-precision decimal number from 0 to 1) and the confidence percentage of neutrality (double-precision decimal number from 0 to 1). Out of the 22,425 event descriptions, we detected the following overall sentiments:

- Negative Sentiments = 18,122
- Positive Sentiments: 95
- Neutral Sentiments: 4,137
- Mixed Sentiments: 71

Fig. 6 shows the overall detected sentiment of the events on the country of origin. Since more than 80% of global events were detected as negative in sentiment, we proceeded with assessing the level of negativity of these events. The confidence of negativity of the events was applied on each of the detected entities, and the results are shown in Fig. 7.

In terms of region, the Eastern Mediterranean (containing Syria, Lebanon, Turkey, Israel, Jordan, Palestine, and Cyprus) had the highest score, followed by the Gulf States, South Asia (containing Afghanistan, India etc.), and other regions, as shown in Fig. 7(e). Fig. 7(d) shows the top 10 countries associated with the most negative events, which are Syria, Iraq, Myanmar, Afghanistan, Yemen, Ukraine, Lebanon, Mexico, India, and the United States, in that order. Location entity analysis showed that Mandalay (in Myanmar), Beirut (in Lebanon), Baghdad (in Iraq), and other locations were

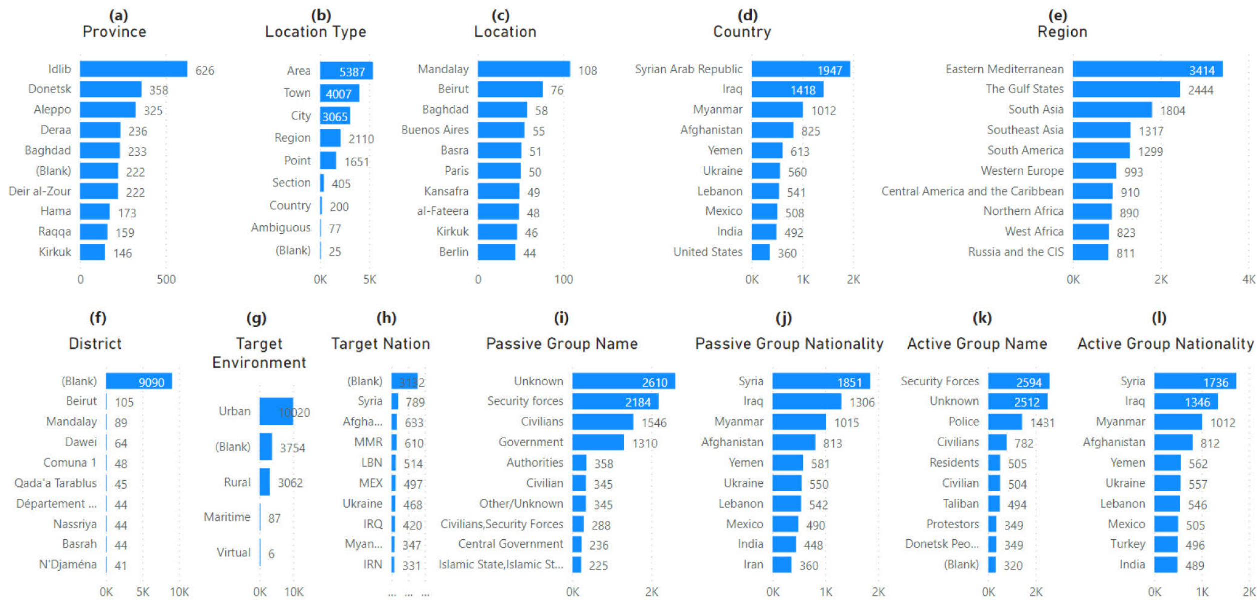

FIGURE 7. Top 10 aggregated negative sentiments on the detected entities.

associated with the most negative global events (Fig. 7(c)). Fig. 7(a) shows that the top three provinces associated with the most negativity were Idlib province (in Syria), followed by Donetsk (in Ukraine), and Aleppo (in Syria). Similarly, Fig. 7(i) and Fig. 7(l) show that worldwide, most negative events were performed by actors from Syria, Iraq, Myanmar, Afghanistan, Yemen, Ukraine, Lebanon, Mexico, Turkey, and India.

Hence, AI algorithms allows the users of the system to quickly visualize the most aggressive (i.e., negative) global events by multiple entities, such as Region, Country, Location, Location Type, Province, Active Group Nationality, Active Group Name, Passive Group Nationality, Passive Group Name, Target Nation, Target environment, and District.

Fig. 8 shows our implementation of explainable AI with anomaly detection algorithms. Fig. 8(a) explains to the user in plain natural language that on Friday, July 16, 2021, the negative confidence of event description was unexpectedly high with a value of 116.84, which was beyond the expected range of 61.62 to 102.16. Fig. 8(a) also shows that this particular anomaly may be attributable to two factors (using AI to perform root-cause analysis): '*Region' is Oceania* with 11% confidence strength and *'Passive Group Nationality' is New Zealand* with 9% confidence. When we click on the first identified factor (i.e., '*Region' is Oceania*), the system explains in plain language (using Microsoft NLP) that on this particular day the negative sentiment associated with the Oceania region was unusually high, which may have lifted the overall negative sentiment on that day (as shown in Fig. 8(b)). Further, with the help of a line graph visualization, the explainable AI demonstrates the overall negative confidence by time against the negative confidence associated with *region* = *Oceania* by time (as shown in Fig. 8(b)). Similarly, Fig. 8(c) explains in plain text and visualization that on that particular day, there was a surge in negative sentiments for which the passive group nationality was New Zealand. Hence, our implementation of explainable AI uses natural language texts and visualization to explain the AI's root-cause analysis process on the detected anomaly.

VI. DISCUSSION

The proposed system we designed is sufficiently robust to support a wide range of scenarios by selecting any combination of detected entities (i.e., E_1, E_2, E_3, …, E_{12}) combined with any selection of dates. We first need to calculate the possible filter combinations. For example, if a feature has three possible values, A= {*Apple*, *Orange*, *Topple*}, it appears that there could be the following filter combinations: 1) {Apple}, 2) {Orange}, 3) {Topple}, 4) {Apple, Orange}, 5) {Orange, Topple}, 6) {Apple, Topple}, 7) {Apple, Orange, Topple}.

Therefore, for A, there are seven possible filter settings as represented by $(2^{|A|}-1)$, in which the formula for calculating the power set of A minus 1 (i.e., $P(A)-1$), where |A| is the cardinality of A and 1 is deduced because the power set also includes an empty set, and the presented system does not support the selection of an empty set.

Table 2 shows the cardinalities of E_1 to E_{20}. Moreover, we tested our solution for 92 days (from June 2, 2021 to September 1, 2021). Hence, the total number of possible scenarios for our global events can be calculated as follows:

$$|L| = \prod_{m=1}^{M}\left(2^{|E_m|}-1\right) X(2^{91}-1) \approx 2.76X10^{8404} \quad (15)$$

Fig. 9 shows an explainable AI in working for a particular scenario (out of these 2.76×10^{8404} possible scenarios), where the region was filtered for "The Gulf States". As Fig. 9

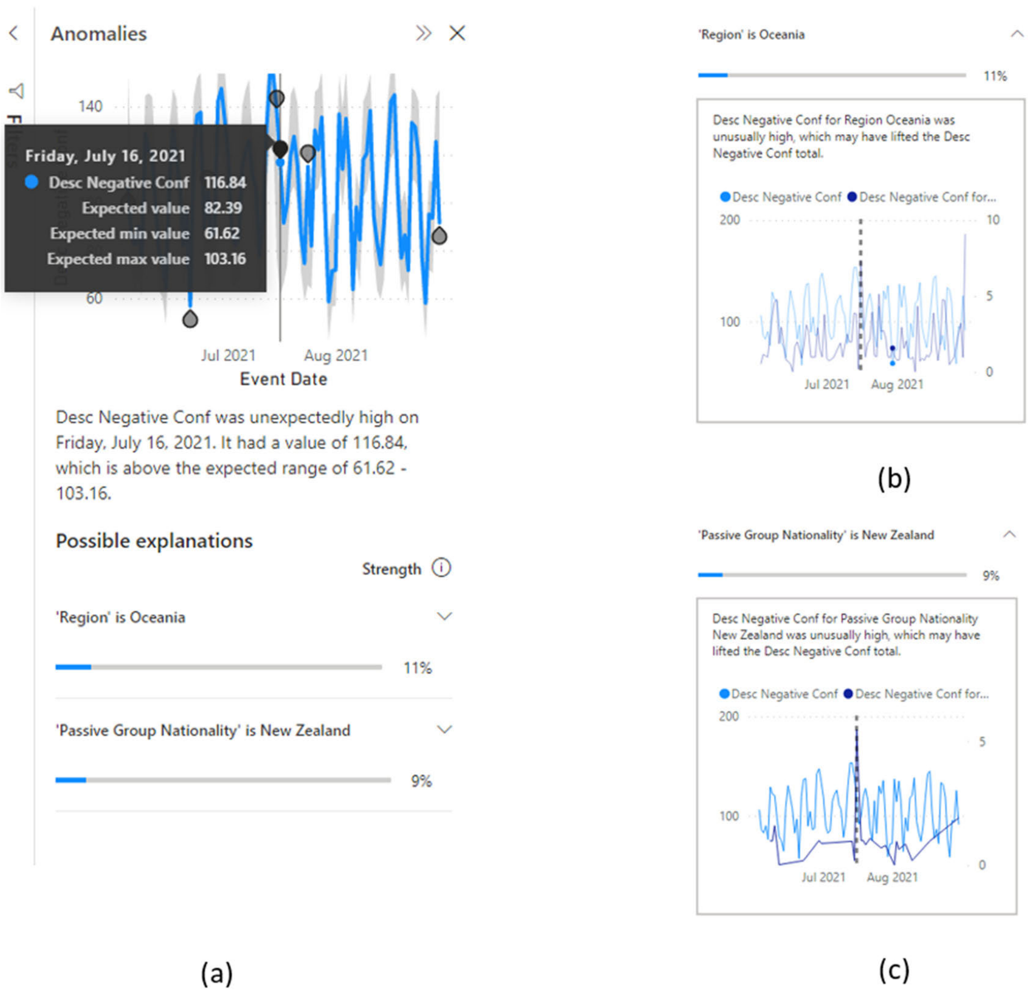

FIGURE 8. **Explainable AI implemented with Anomaly Detection, where the root cause of the anomaly is explained in plain natural language in Text and associated Visualization is displayed to the user.**

shows, an explanation is first provided to the user that the negative confidence sentiment on Tuesday, July 20, 2021, was unexpectedly high with a value of 49.71 (outside the expected range of 27.65 to 37.63). Then, with the help of natural language and visualization, Fig. 9 explains the reason for the high negative sentiment on that day. The dynamic explanation provided by the system makes it clear to the user that on that particular day, "*Khuzestan*" province in Iran had a higher number of events with high negative sentiment confidences. This level of granularity for the proposed explanation was possible since entity detection and sentiment analysis provided contexts to the event description.

During our experimentation, we observed that a few terms were incorrectly classified as location entities (i.e., false positives) and a few valid location entities could not be identified as location entities (i.e., false negatives) by our implementation of AI algorithms. Therefore, to assess the performance of our algorithm and system, we used several evaluation metrics, including True Positive (TP), False Positive (FP), False Negative (FN), Precision, Recall, and the F1-score.

Accuracy provides the overall accuracy of the model, and it is represented by the fraction of the total samples that were correctly classified the by the classifier, as shown in (16):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

Precision indicates the fraction of predictions as a positive class that were actually positive, as shown in (17).

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

Recall shows the fraction of all positive samples that were correctly predicted as positive by the classifier, as shown in (18). It is also known as the true positive rate (TPR), sensitivity, and the probability of detection.

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

The F1-score combines precision and recall into a single measure, as shown in (19). Mathematically it is the harmonic mean of precision and recall.

$$F_1Score = \frac{2XPrecisionXRecall}{Precision + Recall} = \frac{2XTP}{2XTP{+}FP{+}FN} \tag{19}$$

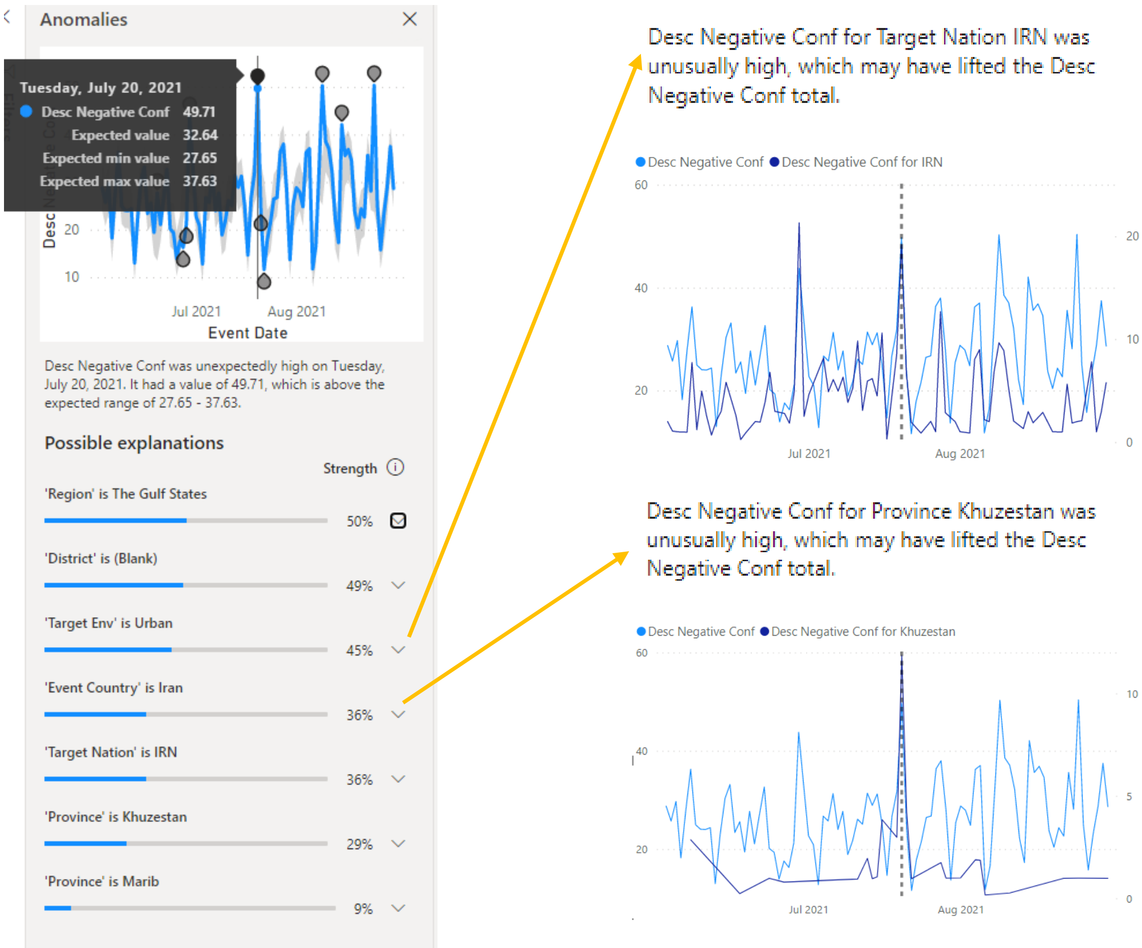

FIGURE 9. **AI-based anomaly detection explaining the reasoning with natural language and charts.**

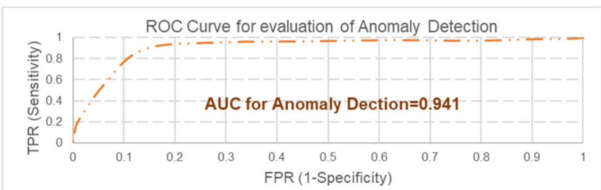

FIGURE 10. **Accuracy of the anomaly detection algorithm with explainable AI was found to be 0.941 (AUC).**

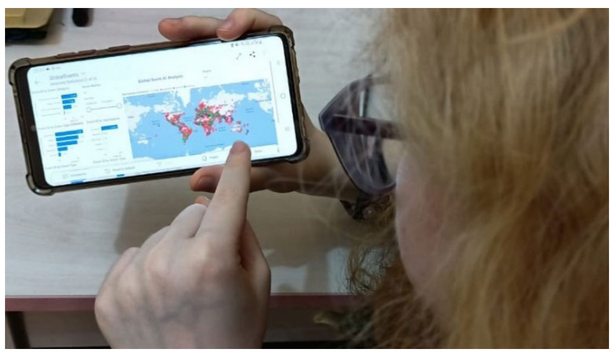

FIGURE 11. **AI based anomaly detection on global events deployed on mobile environment.**

The detailed performance evaluation of the proposed algorithm and system is provided in Table 3. As this table shows, two entity types, region and target environment, performed the best in terms of precision and recall (i.e., both were 1). District had a precision of 0.995 and recall of 0.997 with an F1-score of 0.996. The overall accuracy of the entity detection algorithm was 0.994 in terms of the F1-score. Last, the receiver operating characteristic (ROC) curve in Fig. 10 illustrates the diagnostic ability of the anomaly detection algorithm with explainable AI (binary classifier system). The AUC was found to be 0.941, which proves the higher accuracy of our automated situational awareness system with explainable AI in comparison with the information classification algorithms reported in [1].

VII. USER NOTES

The ML-based knowledge-discovery solution presented in this study was implemented using Microsoft Power BI, which is freely available for download from https://app.powerbi.com/. The user can access and download the complete source files (.pbix) from the Author's hosted Power BI dashboard

TABLE 3. Performance evaluation of the entity detection algorithm.

Detected Entity Types	TP	FP	FN	Precision	Recall	F1-score
Region	18	0	0	1	1	1
Country	192	0	1	1	0.995	0.997
District	3655	17	11	0.995	0.997	0.996
Province	2324	12	16	0.994	0.993	0.994
Location Name	11668	81	14	0.993	0.999	0.996
Location Quality	9	1	0	0.9	1	0.947
Active Group Name	4322	37	42	0.991	0.990	0.991
Active Group Nationality	257	19	16	0.931	0.941	0.936
Passive Group Name	4395	56	38	0.987	0.991	0.989
Passive Group Nationality	540	21	9	0.963	0.983	0.973
Target Environment	5	0	0	1	1	1
Target Nation	442	19	4	0.959	0.991	0.975
Total	27827	263	67	0.990	0.997	0.994

at [40], [41]. After downloading and opening the entire solution using MS Power BI Desktop, the user can host the solution to either Microsoft Cloud or within a local network for making it available to other researchers or strategic planners.

The typical users of this system are strategic planners, policymakers, and diplomatic strategists who are concerned with global events and their subtle impact on society, groups, and locations (applicable for 192 countries). This system would allow users to understand the characteristics of global events in a particular area and provide useful guidance for policy implementation and diplomatic ties with affected groups, governments, and non-government entities.

VIII. CONCLUSION

This paper provided a detailed methodological framework for creating contextual information on unstructured global event descriptions by using AI services such as entity detection and sentiment analysis. With this auxiliary contextual information, AI algorithms, including anomaly detection algorithms, can successfully detect abnormal patterns in time-series data and perform a root-cause analysis with explainable AI. Using the methodology described in this paper, we designed, developed, and deployed a system based on ML .Net and Microsoft technologies [15], [38], [39]. The deployed system was capable of critically analyzing 22,425 global events and highlighted abnormal patterns. Moreover, this system could successfully explain the root cause of these abnormalities by using textual information in natural language and visual graphs. The proposed methodological framework resulted in an automated media analysis system that was proven to be both robust (i.e., capable of dealing with 2.76×10^{8404} dynamic scenarios) and accurate (i.e., entity detection had an F1-score of 0.994 and anomaly detection had AUC of 0.914). The proposed solution was also deployed in mobile environments on both Android and iOS platforms providing remote accessibility towards the users of the system, as seen from Fig. 11.

Using the proposed solution, a strategic decision maker working in the defense sector or in government agencies can make evidence-based policy decisions. Other than policymakers, local news agencies and reporters can also benefit from the presented system, since this system can efficiently and effectively highlight critical events with more negative impact compared with thousands of regular events.

In future, we would like to augment the functionalities of the presented global event monitoring system with additional AI algorithms so that global threat maps could be generated for any number of scenarios.

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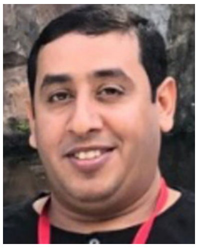

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