ETL and BI in Military-Civilian Collaboration for Disaster Preparedness

Shiva Kumar Vuppala

Senior Sql Developer, Celina, Texas, USA
ORCID: https://orcid.org/0009-0004-7845-8975

Abstract: ***In the face of increasing climate-related catastrophes and large-scale emergencies, the need for seamless coordination between military and civilian agencies has become more critical than ever. Effective disaster preparedness relies heavily on the ability to integrate, analyze, and act on diverse data sources. However, traditional systems often suffer from fragmented data silos, inconsistent formats, and slow decision-making processes, hindering timely and coordinated responses. This paper explores the application of Extract, Transform, Load (ETL) processes and Business Intelligence (BI) tools as a robust framework to bridge this operational gap. ETL pipelines are used to collect and standardize data from weather agencies, emergency services, defense systems, and non-governmental organizations (NGOs), transforming it into a structured format suitable for analysis. Once integrated, BI platforms generate real-time dashboards, predictive models, and visual reports that enhance situational awareness and facilitate proactive decision-making across agencies. The proposed method also includes the implementation of an MLP-LSTM architecture for forecasting critical disaster variables, such as casualty rates and resource needs, based on historical and real-time data. By combining temporal sequence learning with complex feature extraction, the model significantly improves the accuracy and speed of disaster impact predictions. Real-world scenarios, including responses to hurricanes and wildfires, are used to validate the effectiveness of this approach. Graphs illustrating improvements in data quality, loading time, response efficiency, and reduced casualties further reinforce the benefits of this system. Despite the advancements, limitations remain in terms of interoperability, data privacy, and the need for real-time automation in some legacy systems. Future work will focus on enhancing AI-driven ETL processes, incorporating IoT-based real-time feeds, and establishing standardized data-sharing protocols across jurisdictions. Overall, this study presents an integrated, data-driven model that strengthens disaster readiness and response through improved collaboration between military and civilian infrastructures.***

Keywords: Disaster Preparedness, ETL, Business Intelligence, Military-Civilian Collaboration, MLP-LSTM, Real-Time Analytics

1. Introduction

Disaster preparedness and response would require military-civilian cooperation to be stabilized more than ever. In disaster management, disaster response refers to the near real-time integration of a wide variety of mostly contradictorily sourced data, such as weather forecasting and geographical impact assessments of infrastructure, health metrics, public safety communications, and the logistical supply chain [1]. To be effective, decision-making, and coordinated action, even under severe time pressure, are expected to run on their highest levels across many sectors: prosecution of information and agility are often thwarted by sorely outdated operational silos of military and civilian operations that concede little space for existence outside their well-defined parameters. By their nature, disasters cut across jurisdictional, geographic, and organizational boundaries; therefore, the weaknesses of such fragmented systems cannot be far from sight. At the same time, emerging technologies centered on data management and real-time analytics are confronting this challenge with serious impact in shifting the very landscape of inter-agency collaboration. Whereas ETL processes along with BI tools are now thought to be the major driving factors behind these two technologies, ETL systems furnish the administrative backbone needed to combine highly diverse datasets into a common and accessible form, while BI platforms essentially provide meaningful insights from such consolidated information offering: predictive analytics, dynamic visualization, and reporting capabilities [2]. These technologies would allow military/civilian agencies to surmount the barriers that inhibited collaborative efforts, all together with a common data-focused situational awareness contributing to better operational readiness, resource allocation, and beneficiaries' situation during emergencies.

They form the core of foundational architectures for effective military-civilian collaboration for disaster preparedness and response: Extract, Transform, Load, or ETL processes. ETL is essentially an exercise in data gathering, cleansing, and integration from a broad range of sources, both heterogeneous and dissimilar [3]. Military agencies may house high-value national treasures like satellite imagery, intelligence reports, advanced logistical tracking data, and secure communications networks, whereas civilian agencies often manage those data types that are vital in local emergency services, public health metrics, weather forecasts, critical infrastructures, and more. Examples include those dealing not only with operations but also with policy assessments and plans for managing local to those at the global level. But ETL pipelines are required to get those disparate datasets and their original dispersal sources quickly, applying transformation techniques on the data using a more advanced approach for standardizing the formats through data cleaning from inconsistency, removing redundancy, and enriching the dataset in more environments with context metadata [4]. The interoperable data are ready for this process and hence create an all-inclusive and accurate assessment of the situation in transformation. Consequently, the newly transformed data is loaded into centralized databases, into data lakes, or onto cloud platforms secured against any unauthorized entry and using which real-time access is provided to the military and civilian agencies. A common operational picture for all decision-making levels is created from this pool of data because it shares synchronized, trustworthy and well-updated information, which is indispensable when making scenarios for coordinating response efforts, deploying resources efficiently, and mitigating the impacts of disasters on affected populations.

Business Intelligence (BI) tools build on the unified cleansed datasets generated by ETL processes and are used to obtain actionable insights through rigorous analysis, modeling, and visualization. Modern BI platforms like Tableau, Power BI, and Qlik understand vast, complex, and dynamic disaster-related data [5]. They convert raw data into intuitive dashboards, interactive geospatial maps, predictive analytics, and customized reports that give decision-makers situational awareness in real-time to quickly understand the scope and effects of a disaster, detect new threats, and evaluate vulnerabilities. BI tools facilitate the risk modeling and impact assessment necessary to inform decisions on the strategic allocation of resources, optimize deployment of emergency response teams, and improve coordination of humanitarian aid. With its predictive capacity, BI therefore adds to an organization's ability to be proactive [6]. Agencies can now anticipate issues, pre-position important supplies, shore up weakened infrastructure, and provide timely warnings to at-risk populations. The ability to move quickly from collecting data to taking informed action will be critical for the minimization of disaster effects and the enhancement of community resilience.

A special case is the U.S. government's response to Hurricane Katrina in 2005, which underlined the immediate necessity for effective integration of ETL and BI. The event showed the catastrophic failure of data management and inter-agency communication where mismatched and incompatible information systems delayed situational awareness, diverted crucial resources, and prompted organizational confusion between military and civilian responders. The unavailability of timely and accurate data sharing came in thousands of unnecessary hardships against the larger backdrop of ineffective rescue and recovery operations. This historical fiasco primed an interrogation into disaster management at the national level and reflected on the changing fortunes that integrated technological solutions would soon offer [7]. With the constitution of modern ETL pipelines and state-of-the-art BI platforms, an interagency centralized and interoperable information environment is now being fashioned. Such structures indicate a natural fosterer of real-time coalition work, upon which comprehensive threat analysis can be based, allowing decision-makers in both military and civilian sectors to operate on a common and trusted data bed, allowing an effortless transition from a dispersed and disparate database to clear-cut disaster response operations marked by speed, coordination, and effective realization.

In the long run, the coupling of BI tools driven by AI and almost entirely automated ETL pipelines promises to change the whole face of civilian-military cooperation for disaster preparedness and response. Predictive analytics enhanced through artificial intelligence and machine learning models would allow early recognition of even those patterns that signal events as terrible as floods, wildfires, earthquakes, or hurricanes [8]. Therefore, it may predict the very possibility of a disaster and its likely effects on desks and vulnerable populations so that it can better prepare action, pre-emptive action based on assessment or forecasting. The activities of automatic ETL, however, make data production and processing as easy as possible by minimizing human attachments [9]. In this way, it reduces errors and fastens the time taken to transform to clean, reliable datasets, ready for analysis. The proliferation of data warehousing solutions based in the cloud has made it possible for continuous, real-time access to shared datasets between military and civilian agencies, independent of any geographical location, thus ensuring a constantly updated operational picture, a must-have for adaptation to fast-changing disaster scenarios. Each of the above technological advancements lowers or perhaps vastly transforms traditional forms of preparedness into speedier, more intelligent, and adaptable preparatory efforts within the larger scheme of things in the future.

ETL and BI technologies are the most significant key elements for making the transition from a preponderantly reactive approach to disaster management to a more proactive, intelligence-driven approach. By bridging these long-existing data and communication divides between military and civilian groups, these systems create a unified, agile framework that supports improved situational awareness, accelerates coordinated responses, and enhances the effectiveness of rescue, relief, and recovery efforts. Investing in the continual upgrading of ETL and BI capabilities is the luxury of the past; today, it is imperative for national security and community resilience. Future disaster management strategies must be replete with technological integration to ensure that all stakeholders, ranging from federal agencies to local responders, operate within a shared real-time understanding of dynamic situations [10]. An especially robust, seamlessly integrated ETL and BI infrastructure will help military and civilian teams act in concert and cohesion to lessen the damages to lives, infrastructure, and economies caused by the relatively unpredictable incidence of natural disasters.

The Key contributions of the article are given below,

- Developed an integrated ETL framework to collect, standardize, and transform data from diverse sources, including weather agencies, emergency services, defense systems, and NGOs, enhancing disaster preparedness and response coordination.
- Implemented BI tools to generate real-time dashboards, predictive models, and visual reports, enabling improved situational awareness and proactive decision-making across military and civilian agencies.
- Designed and applied an MLP-LSTM architecture for forecasting critical disaster variables, such as casualty rates and resource needs, significantly improving prediction accuracy and decision-making speed during emergencies.
- Validated the system through real-world disaster scenarios, including hurricanes and wildfires, demonstrating improvements in data quality, response efficiency, and casualty reduction.
- Identified and addressed challenges related to interoperability, data privacy, and the automation of legacy systems, laying the foundation for future improvements in AI-driven ETL processes and real-time data integration across jurisdictions.

This document is organized as follows for the remaining portion: Section II discusses the related work. The recommended method is described in Part III. In Section IV, the experiment's results are presented and contrasted. Section V discusses the paper's conclusion and suggestions for more study.

2. Related Works

A. Role of ETL

Li et al. [11] primarily deals with the integration of military and civilian resources within Chinese civil-military systems and addresses optimization for emergency supply allocation and storage. The two-stage stochastic programming technique that develops this is designed to achieve strategic military-civil storage, meaning less reserve costs. An improved version of IWOA is suggested for the resolution of this model with various other techniques. A real case from Tangshan, China, will demonstrate that significant cost savings are made by the joint military-civil strategic reserves if military storage costs are less than 1.5 times those of civilian facilities. The work also emphasizes how decision-makers would need to vary maximum rescue durations according to emergency-specific requirements.

Ronik Ketankumar, Sharareh, and Mostafa 2020) [12] generalize the readiness and exposure of university students to disasters, given that there are almost no disaster risk reduction measures on many campuses despite increasing awareness. Then, a literature review and an online survey, which had 111 subjects, formed a basis for constructing a framework measuring how well students would prepare for disasters by linking their perceptions of obligations regarding safety during a disaster with personal attributes (gender, qualification level, and disaster preparedness knowledge). Among key results from the study are a past education of students in preparation for disasters influences the perception of the need for a compulsory DRR course, and the difference between the two graduate and undergraduate groups was whether the provision of first aid equipment was sufficient. By these outcomes, the study stands to moderate policymakers on how to improve emergency preparedness in campus facilities as well as develop DRR programs in higher learning institutions.

B. ETL in Disaster Management

Patel et al. [13] studied the impact of sociodemographics on students at universities as well as disaster DPI on students' knowledge of disaster risks and ability to cope with emergencies. To understand the influence of these attributes on disaster awareness and preparedness, an elaborate survey with 111 responses was used and analyzed through structural equation modeling. The findings suggested that emergency procedures had an impact on student readiness, while university courses played a greater role in disaster awareness. In addition to supporting policymakers in strengthening emergency preparedness policies and protocols, the presented research was directed toward helping university stakeholders identify critical DPIs to improve programs and develop successful DRM courses.

The present study by Ao et al. [14] in Sichuan Province, China, basically evaluates the link between rural residents' flood experience, attitude, and disaster preparedness behavior to climate change and flooding issues. Usually, residents have poor disaster preparedness behavior according to ordered logistic regression and exploratory factor analysis-based studies. Income level is negatively associated with preparedness while factors like age, education, and length of stay in the area are found to be positively related to preparedness. The preparedness behavior also depends on people's attitudes towards disasters and their past experiences with flooding. The study combines some structural flood management measures with normal preparatory actions such as psychological counseling in flood-prone areas, on-the-go flood warnings, and education about flood preparedness among residents to build resilience and trust in flood management programs.

C. Impact of Disaster

Richmond, Tochkin, and Hertelendy [15] conducted on a national scale, among EM experts, this study determines how frequent and effective the disaster preparedness initiatives in Canada's healthcare institutions are regarding COVID-19. Out of the 161 responses to the poll, which urged that 93% of the respondents had the identity of EM responsibilities. Reviewing frameworks for infectious diseases was the most popular activity covered by 82% of respondents, while the least popular was simulation exercises with only 26%. More commonly, a singular "incident commander" was responsible for incident management within COVID-19: 61%, while only 68% of individuals holding leadership positions underwent training. By this research, more rates and efficacies for disaster preparedness were observed in companies with proficient coloring executives.

Interval type-2 fuzzy sets along with the best-worst method were utilized by Celik [16] to study shelter site selection for disaster preparedness to effectively manage uncertainty and simplify pairwise comparisons. Nine disaster experts having field experience in places like Sivrice, Pazarcık, Elbistan, and Syrian refugee camps directly contributed to the evaluation of six major criteria and twenty-five sub-criteria, determined based on literature review. The analysis highlighted the closeness to be of paramount importance as the most important primary factor while distribution center capacity, logistics personnel availability, energy availability, distance to populated regions, and landslide and flood hazards were the most important sub-criteria. The study recommends that, for effective disaster preparedness, managers and responsible organizations should rank high on these criteria when selecting sites for temporary shelters.

D. Role of ETL in Military

Semlali, El Amrani, and Ortiz [17] demonstrate that due to the enormous volume, near-real-time creation, and complex structures of satellite data in applications such as air quality monitoring, climate change tracking, and disaster predictions, it is considered BD. The authors developed software solutions more concentrating on ETL processes, especially on the ingestion layer of effective integration solving the challenges of RSBD management. The proposed tool will continuously process incoming data approximately eliminating 20% of wrong datasets and 86% of unnecessary files. Thus, the method incorporates the cleaned datasets into HDFS for further analysis of drastically reduced storage requirements and improved data quality.

This pilot study by Firmansyah et al. [18] comprises a sample of male first responders, current duty troops with and without PTSD, and veterans of the armed services who were studied for differences in psychosocial, ANS, HPA axis, and inflammatory responses to high-intensity exercise. Measurements were taken before, during, immediately after, and up to 48 hours post-13-minute high-intensity boxing during the participation of eight subjects (average age 50.1 years). Although effects on psychological aspects like depression, anxiety, and stress, were observed with a lack of clarity in salivary biomarkers, results indicated pronounced ANS changes such as meaningful to very large degrees of deceleration in HRV lasting time up to 48 post-exercises. Proposed results have indicated that high-intensity exercise might induce persistent stress-related ANS change among sufferers of PTSD.

3. Research Methodology

1) Research Gap

Despite the advancements made in terms of ETL and BI technologies applied to disaster preparedness, there linger critical research gaps and constraints in existing trends that deter the full potential of military-civilian collaboration being attained. ETL is typically slow, struggling with real-time data ingest and transformation when it comes to heterogeneous, unstructured, and rapidly changing datasets-one major character in disaster scenarios- leading to delays in intelligence being productive [19]. Quite a number of the BI tools are great but usually have post-event analysis in their core development rather than being about dynamic, predictive decision support in crises as they happen. Furthermore, interoperability between military and civilian data systems from disparate data standards, security protocols, and organizational cultures has inhibited free information exchange. Current frameworks interface poorly with data trustworthiness and quality concerns when dealing with the integration of data from nontraditional or crowd-sourced civilian media [20]. Neither are there well-defined and full-scale models for determining the adaptation of ETL and BI processes to different scales and complexities of different disasters. Few studies have closely examined ethical, legal, and operational complications in the sharing of real-time information from the military to civilians and vice versa, especially about data privacy and command hierarchies. The above weaknesses show glaringly the need for research into more adaptive, automated, and secure ETL pipelines that support the development of next-generation BI tools with predictive capabilities for cross-agency collaboration and real-time decision support in rapidly changing environments.

2) Proposed Framework

The enhanced workflow is designed in Fig 1 to include ETL processes and BI tools that will facilitate military-civilian interaction in disaster preparedness and response. The first point in the workflow is Data Collection when information is being gathered from various sources terms as satellites, weather, emergency management systems, and even civilians. This would be a very important stage in the establishment of a multi-dimensional data foundation. The processing of this information splits it into Data Pre-Processing: tasks like cleaning, formatting, and normalization are performed to ensure that the inputs are consistent, accurate, and ready for analysis. This is then followed up by Data Loading into central systems or supported cloud storage, thereby making organized and safe access possible for analyzing and further data processing. One of those mentioned above stages is Military-Civilian Disaster Prediction, where next-generation machine learning techniques MLP-LSTM models are deployed to predict possible disaster impacts and scenarios. This predictive capability will be rich in preparedness by offering early warning signals and data-driven resource allocation. Then turns its role around to Business Intelligence, referring to the process of transforming predictive and historical data into meaningful insight with the help of the use of dashboards, reports, or real-time monitoring systems to promote faster and more coordinated disaster response efforts through the use of BI tools. At last, comes the Case Study section in which certain disaster scenarios will be studied to validate the effectiveness of the workflow, showing which areas would require improvement, and showcasing practical applications of the ETL-BI integration framework. Figure 1 anticipated a simplified, yet thorough technology-undergirded approach, thus augmenting agility, efficiency, and accuracy in disaster management collaboration.

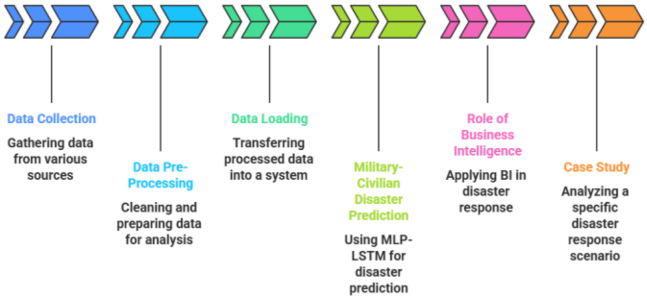

Figure 1: Proposed Framework

3) Data Collection

There are many sorts of data about disasters or calamities such as emergency management records, meteorological patterns, geospatial data, infrastructure status, military assets, health data, and supply chain logistics information which can be used from Kaggle datasets. These datasets can well demonstrate how ETL and BI tools could facilitate military-civilian interaction during disasters for preparedness. The datasets allow you to integrate various types of data: including past disaster incidences, real-time weather forecasts, geospatial mapping of affected areas, infrastructure damage, healthcare availability, and resource allocation. With the unification of such datasets through ETL processes and predictive analysis with BI tools, agencies can effectively enhance their efforts in forecasting disaster effects, coordinate effective response actions, and optimize recovery efforts.

Dataset Link:
https://www.kaggle.com/datasets/jseebs/disaster-dataset

4) Data Pre-Processing using Min-Max Normalization (Transform Phase)

In the context of disaster databases, the pre-processing stage is very vital in making the dataset ready for analysis as well as in ensuring that it is in good format for predictive modeling. One example of Min-Max Normalization is an important technique in this phase when datasets are characterized by features with different scales. For instance, weather parameters like wind speed or rainfall levels are often not in the same range compared with other infrastructural data such as road damage severity or hospital bed capacity. Therefore, Min-Max Normalization can be applied to rescale the normal features' value range to the target common interval, usually between 0 and 1. This prevents an individual feature from having a decided outsize impact on the analysis or performance of the model because of the scales. The transformation facilitates the model to learn patterns from all features more equally compared to unnormalized data, particularly when the machine learning model uses distance-based algorithms or gradient-based optimization methods, with unnormalized data creating bias. It is given in Eq. (1).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

All features are brought to a comparable scale by scaling them within the range of 0 and 1. A piece of this procedure calculates the min and max for features available in the data set. Thereafter, the conversion transforms the values of each feature within the range of 0 and 1. This process ensures that all sole features are brought into comparable scales so that the data can get more impressive and lucid for analysis compared with other methods. Min-Max normalization comes in handy in disaster management applications, whereby data are collected from a plethora of data sources, such as weather data, geospatial data, and military asset data with different measurement units. For example, the temperature can vary from -10 to 45 in centigrade, whereas the number of available hospital beds can be from 0 to 1000. After applying Min-Max Normalization, both of these features will be normalized to the same scale, equalizing the treatment by machine learning models hence improving their predictive accuracy. The model thus obtained would be more robust, less sensitive to outliers, and capable of providing reliable predictions for disaster preparedness and response strategies.

5) Data Loading (Load Phase)

Once the data has been pre-processed and normalized, the next major component of the ETL pipeline is the Load Phase during which the transformed data now gets loaded into the target system's centralized data warehouse, a cloud storage solution, or a dedicated disaster management platform. However, loading this data in the context of civil-military collaboration toward disaster preparedness should be done with utmost precision, letting all agencies be able to tap into clean, consistent, and updated data for on-time decisions. Integrated analysis, predictive modeling, and visualization are made possible by the data warehouse or cloud repository. Loading typically requires maintaining data integrity during the load phase, i.e., no corruption, duplication or loss occurs at all during the transfer. With traceability and transparency in mind, the primary datasets are often loaded with metadata such as data source, timestamp, and transformation details. In disaster preparedness scenarios, a large number of agencies like the weather department, emergency response agencies or services, public health services, and military logistics units depend heavily on the accuracy and consistency of this data loaded for speedily coordinating, allocating resources, and forecasting disaster impacts. Thus, an effective load mechanism that can support both batch and real-time data intake would be vital, especially in situations where continuous updates could be very important for response efforts, for instance, when the weather conditions or infrastructure status keeps evolving.

Data loading may be different in its regard relative to the urgency of a disaster scenario as well as the architecture of a system. On the other hand, batch loading refers to the loading of large volumes of data collected over a period and brought into a system all at once: an operation more often associated with historical analysis and fairly long-term adjusted strategic planning. Real-time or near-real-time loading accommodates instant updates as new data becomes available, which also includes loading in the case of dynamic disaster response operations wherein decisions are rather made quickly. For example, when a hurricane occurs, real-time loading of weather information, alerts of flood stages, and evacuation statuses into a common system would enable both military and civilian agencies to watch developments and modify their actions accordingly. Validation checks for formats and quality compliance for incoming data may also form part of the load process. Reject corrupt records and log errors for further examination. Security measures such as encryption and access control assure confidentiality and integrity and are therefore imperative in highly sensitive environments such as military-civilian collaboration. The load phase not only terminates the ETL cycle but also begins a new approach to advanced business intelligence operations which will allow the joint forces to use predictive analytics, dashboards, and alerts for a much better disaster preparedness and response strategy.

6) Military-Civilian Disaster Prediction Using MLP-LSTM

The Military-Civilian Disaster Prediction-based MLP-LSTMs deal with two aspects of disasters, one temporal and the other spatial. Spatial static features, such as geo-referential and infrastructural information, are learned by the MLP, while LSTM learns the active time series data, such as data on forecasted weather conditions and seismic activities. The outputs from both networks are incorporated together into the predictive model, and then using a loss function, the predictions are optimized for accuracy and execution of the management strategies jointly with military and civilian entities in terms of disaster management.

Input Representation

Input representation in the proposed system associated with disaster management intrinsically involves heterogeneous domains such as historical data, real-time sensor information, satellite imagery, weather reports, emergency call logs, and logistics data about military and civilian aspects. These sets of inputs are subjected to different preprocessing mechanisms and encoded into suitable structured formats for ETL operations and machine-learning models. Initially, categorical variable values are label-encoded or one-hot encoded, and then numerical values are normalized so that the different features can be brought to a common standard. In addition, temporal data such as time-stamped incident logs and weather patterns make their way to sequences amenable to LSTM-type processing for the system to intuit time-dependent patterns. This multi-modal, structured input representation is, therefore, helpful in providing a broad span of disaster variables conducive to prediction and robust real-time decision-making.

MLP Layer

In the present research, the role is played by the layer MLP to convert the structured data input into high-level feature representations representing the underlying patterns necessary for disaster impact forecasting. After extracting, transforming, and loading from several sources through the ETL process, the MLP layer will involve the primary learning phase of the proposed MLP-LSTM architecture. It consists of several fully connected layers applying conflict non-linear activation functions (which are commonly ReLU) that map and learn the complex relationships among such features as weather severity, population density, resource availability, as well as the vulnerability of infrastructure. This allows the model to be able to learn those significant interactions and correlations that are frequently ignored by conventional modeling. Therefore, in reality, the MLP is a powerful feature extractor that compresses and transforms the raw input variables into an abstract, information-laden vector that can be further efficiently processed by the temporal learning component (LSTM). It is given in Eq. (2).

$$h_{mlp} = \sigma\left(W_1 X_{spatial} + b_1\right) \tag{2}$$

LSTM Layer

From modeling the evolving nature of disasters, the LSTM layer, described in the proposed system, is responsible for the import of temporal dependencies and dynamic patterns across sequential data. The LSTM layer learns greatly from time sequence data corresponding to modeling disaster variables changing over time, while most neural networks assume independence among all inputs. The MLP layer extracts high-level features from the raw inputs; these high-level features are fed into the LSTM layer, where a sequence of memory cells and gating mechanisms are utilized to retain relevant historical context while also forgetting obsolete information. By remembering long-term dependencies, the model describes how past weather behaviors, emergency response times, and resource consumption impacted future event conditions such as sudden surges in casualties or shortages in supplies.

Specifically, the relevance of the LSTM layer in this work is to provide accurate forecasting of critical disaster parameters concerning time so that disaster response can be made more informed and timely by both military and civilian agencies. For example, the LSTM can assess a series of weather data, response times, and medical supply levels and predict when and where the demand for resources may peak so that assistance and personnel can be preemptively deployed. Such temporal learning becomes crucial in fast-evolving cases like hurricanes or wildfires, where damage conditions evolve every hour, and delayed interventions become fatal. In the architecture of the larger system, the LSTM turns static feature representations into dynamic predictions that drive the real-time dashboards explained in the Business Intelligence (BI) layer, hence ensuring operational readiness and situational awareness. So, the LSTM is at the heart of such an effort that allows the system to step out from static analysis and into proactive and data-driven disaster response. It is given in Eq. (3), (4) & (5).

$$\begin{bmatrix} f_t \\ i_t \\ o_t \\ \tilde{c}_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ tanh \end{bmatrix} (W x_t + U h_{t-1} + b) \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{4}$$

$$h_t = o_t \odot \tanh\,(c_t) \tag{5}$$

Concatenation and Final Prediction

The concatenation and final prediction stages model synthesize the features, learned spatially (MLP) and temporally (LSTM) in the model, to arrive at a single prediction about the occurrence of any disasters. The spatial features, generated through the MLP, provide important steady-state pictures such as those for geography, status of infrastructure, or the environmental state, whereas the time-dependent features learned by the LSTM from sequential data like weather patterns, seismic activity, or historical disasters capture the temporal features. Concatenation involves the outputs of both the MLP and LSTM being spatially or temporally derived hidden states, each representing some learned features. It is given in Eq. (6) & (7).

$$h_{contact} = Concat\left(h_{mlp}, h_{lstm}\right) \tag{6}$$

$$\hat{y} = \sigma(W_o h_{concat} + b_o) \tag{7}$$

Loss Function

The loss function for Disaster Prediction may be said to play a pivotal role in optimizing MLP-LSTM-based network architecture during training. It measures how different the output predicted by the model is from the actual target values-that is, the discrepancy between the predicted and the actual, with the least objective of adjusting every influencing parameter of the model in the downward direction corresponding to the associated error. Binary cross-entropy loss is employed in this case for a task where the prediction could be termed as a disaster or not because this method imposes heavier penalties on the model for misclassifications concerning the presence and absence of disasters. Therefore, minimizing loss implies better reliability of prediction, a key point in successful military-civilian collaboration in disaster preparedness, as timely and accurate predictions can facilitate better distribution of resources and response strategies.

$$\mathcal{L} = -[ylog\,(\hat{y}) + (1-y)log\,(1-\hat{y})] \tag{8}$$

The MLP-LSTM Architecture in Fig 2 shows how hybrid deep learning models are built between Multi-Layer Perceptron and Long Short-Term Memory Networks in the effective processing of disaster time series as well as structured data. Here, initially, in-house input with weather patterns, emergency alerts, and sensor readings is processed in fully connected layers to capture complex nonlinear relations. The MLP output then feeds into learning temporal dependencies and sequential patterns using LSTM layers in the available data. This approach allows for identifying features that can capture their evolution over time, mostly effective in disaster escalation prediction, resource needs, and response timing. MLP-LSTM could thus improve forecasting accuracy and decision support in disaster preparedness scenarios by providing timely insights for military and civilian agencies.

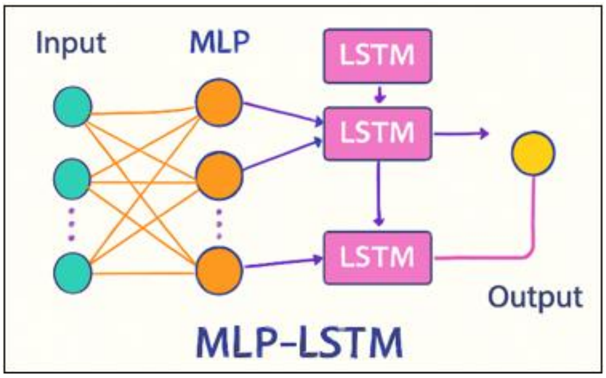

Figure 2: MLP-LSTM Architecture

Role of Business Intelligence (BI) in Disaster Response

In this step, BI tools are specifically used for converting collected and processed disaster data into actionable insights to directly facilitate timely, informed, and coordinated decision-making. This will include the real-time monitoring of disaster conditions via dynamic dashboards, predictive analysis to ascertain how disasters will impact the situation, appropriate allocation of resources as per the changing demands, and coordinating and communicating efforts between military, civilian, and humanitarian organizations. BI platforms bring multiple sources of data into one operational picture by which agencies can follow situations as they develop, anticipate risks, optimize deployments of rescue teams and supplies, and effectively communicate with the public. Moreover, post-response activities will also include using BI tools to evaluate responses and engage in lessons learned from each event to help bolster preparedness for the next.

Real-Time Situational Awareness

BI is the blood of disaster response. It provides real-time situational awareness that's critical for fast, informed decision-making when the situation rapidly changes. Hurricanes, earthquakes, wildfires, floods, and all disasters are very unpredictable; when the information comes late, chaos and mismanagement take place. BI tools brought together all data collected in an organized manner from various sources such as weather stations, emergency call centers, satellite images, social media feeds, geospatial sensors, and field operation reports. BI platforms then consolidate the data into dynamic, interactive dashboards and live reporting systems that can provide both military and civilian agencies with an up-to-the-minute operational picture of the disaster landscape. With what they observe, decision-makers, emergency managers, and field commanders can then identify possible emerging hotspots and forecast the movements and escalation of threats to better target the deployment of critical resources such as rescue teams, medical supplies, and evacuation transportation. Rather than react blindly, agencies can now anticipate needs, adjust strategies in real time, and precisely coordinate action across different units and organizations. Ultimately, if agencies would have to be without BI for real-time situational awareness, they would be severely hampered in their efforts and risk slow reactions, inefficient resource use, and the escalation of loss of life and impact on infrastructure, which indicates how fundamentally important BI has become in the current day disaster response activities.

Predictive Analytics for Resource Allocation

Teaching-learning focused on disaster management by way of business intelligence for forecasting future disaster events and allocation of resources to smartly respond to those events. By using historical records of disasters, understanding the patterns of extreme weather with geographical trends, and using real-time ground data, BI tools run predictive analytics models that can forecast areas that might get severely affected even before they are found to be severely affected by a disaster. Thus, BI platforms would model predictions on poorly affected areas or model severely affected areas based on severe flooding, outages, or mass casualty-type events as environmental changes and demographic vulnerabilities take place. They will predict surge-demanding hospitals, shelters, or critical infrastructure based on real-time patient admission rates or flows of evacuees. This way Military logistics units, humanitarian organizations, public health agencies, and emergency services use predictions to position supplies ahead of a disaster-conducive environment, such as food, water, fuel, medical kits, and rescue equipment. This minimizes last-minute rushes and potential congestion in transport. The efficient resource optimization and time is when mobilization occurs to the benefit of better utilization of scarce resources and enhance the time of response; hence, delivery of assistance to the vastly naive population takes place on time. BI predictive analytics save lives by reducing wastage, reducing operational costs, increasing the effectiveness of interventions with precision, contributing profoundly to the resilience and responsiveness of disaster management systems, and significantly alleviating the humanitarian and financial costs of natural disasters.

Improved Collaboration Between Agencies

An equally critical task of BI in disaster management is enhancing the relationship among multiple civilian and military agencies to ease the workflow through these complex multi-organizations. Most disaster response initiatives involve an enormous and assorted web of actors comprising military units, police forces, fire departments, emergency medical services, NGOs, international aid agencies, and private sector logistics providers. Each of them brings unique capabilities but also respective operational protocols and information systems. BI platforms take care of the differences among these actors by integrating, harmonizing, and standardizing data from various sources into one user-friendly and interpretable environment. Using shared dynamic dashboards, customized reports, real-time alerts, and secure access controls, BI tools allow all actors to maintain a common operational picture of the disaster landscape. This unique visibility removes traditional data silos, reduces bottlenecks in information sharing, and encourages synchronized decision-making across organizations at a time when such efficiency is crucial, especially during high-stress, time-critical disaster scenarios. Thereby, evacuation planning, critical supply chain coordination, real-time communication to the public, and dispatch of emergency teams, among other functions, are aligned, efficient, and targeted. In effect, BI would be in a sense the "universal language" for everyone involved, thus facilitating coordination and ultimately enhancing efficacy and speed for the disaster response efforts overall extent, hence a great number of lives saved and speedy recovery of the affected communities.

Post-Disaster Analysis and Continuous Improvement

As much as the immediate concerns have been taken care of in disaster management, the importance of Business Intelligence (BI) tools is unquestionable when they are put to post-disaster analysis and continuing disaster preparedness strategy development. After stabilizing the crisis phase, military, civilian, or humanitarian agencies will use BI-governed analytics to evaluate their respective response operations thoroughly and to systematically identify areas of strength or critical failures and inefficiencies-as defined by different key performance metrics such as average response times, resource mobilization, public communication reach and accuracy, casualty rates, as well as levels of impact on the built environment. BI has therefore provided a clear and objective view, established on data, onto successes and shortcomings of operations through its dashboards and dynamic reports that analyze an organization's performance on key aspects such as response times, mobilization of resources, reach and accuracy of public communication, casualty numbers, and levels of impact on physical infrastructure to achieve through itself. With this evidence-based approach, organizations are in a position to identify consistent bottlenecks, find hidden weaknesses, and recognize lost opportunities for faster or more effective interventions. Post-disaster recovery will also begin with BI as it would entail the use of the right set of tools for conducting a detailed damage assessment, administering geospatial analyses, and assisting government, donor, and community planners and strategists with prioritization for reconstruction projects and equitable recovery funding allocations in relation with severity and need. It strategizes these raw, disastrous data into meaningful actionable insights, thus, ensuring that every disaster is maximally learned from for better preparedness planning, improved response protocols, enhanced inter-agency coordination, and strong community resilience against future disasters in terms of speed, efficiency, and effectiveness.

Disaster management-related activities-pyramid ETL concerned with BI is shown in Fig 3. This illustration shows how essential agencies' weather data and emergency services, together with defense data, interface with this centralized ETL system, with standardization requirements and structuring for analytical purposes. Thus, these processed data can provide real-time BI dashboards to alert decision-makers about key indicators, upcoming developments, and their most suitable response. Within this context, the figure represents a unified data infrastructure to augment situational awareness and mitigate rapid proactive response in military and civilian sectors in times of emergency.

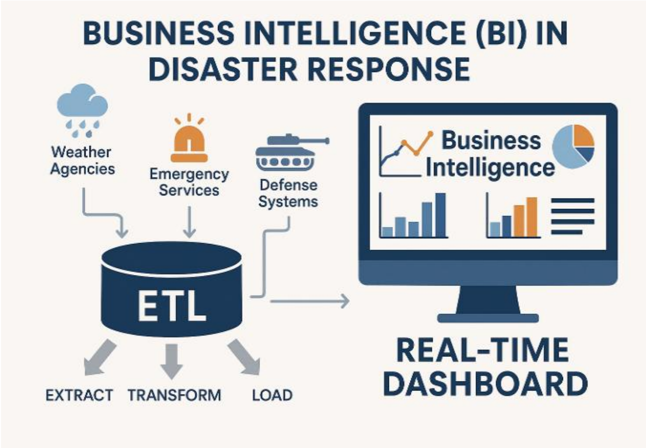

Figure 3: Bi IN Disaster Response

Case Study: The U.S. Government's Response to Hurricane Katrina

Hurricane Katrina hit the Gulf Coast of the United States in August 2005 and exposed very severe weaknesses in disaster preparedness and response infrastructure in the country. The Category 5 storm caused over 1,800 deaths and billions of dollars in property damages, affecting mostly New Orleans, Louisiana. One of the worst mishaps brought by the hurricane was the lack of coordination between federal and local agencies. Warnings were given by meteorological services, but evacuation and deployment of resources and rescue operations were delayed by communication problems and fragmented data systems. The Federal Emergency Management Agency (FEMA), in general, failed to have a platform to assimilate and analyze information from its sources, which hindered timely decision-making and logistics planning during the most critical hours.

The chronic under-preparation and lack of real-time data integration are manifestations of more than the absence of an appropriate ETL arrangement. The data about weather services, emergency calls, hospital capacity, and military assets existed as siloed data, rendering it almost impossible to create any coherent situational image. There was no centralized dashboard to rely on for a predictive model for future forecasting of requirements on resources, and thus all data was being collected via time-consuming manual reporting methods or slow-moving bureaucratic chains. Consequentially, food, water, and medical aid got delayed, with many victims going days without help. Lack of interoperability within systems and poorly flowing information caused massive confusion, misallocation of resources, and degradation in public trust in government institutions.

In retrospect, the Katrina response has been the dynamic factor for reviewing emergency management in the U.S. Had such infrastructure as ETL pipelines, Business Intelligence dashboards, and machine learning models—as in the case of the MLP-LSTM architecture suggested in this study—been operational, officials could have had access to unified data views and real-time analytics for accurate forecasts of impact zones and casualty estimates, thus enabling faster mobilization of military and civilian resources, better distribution of medical and logistical support, and streamlined communications with the public. Hence, the case of Hurricane Katrina shows the urgent need for integrated, data-driven disaster management infrastructures that stimulate timely and collaborative responses among agencies.

4. Results & Discussion

The analysis that follows is a result of a thorough examination of the role of ETL and BI tools in militarizing civilian collaboration during the preparedness and response to disasters. The section illustrates how data integration and real-time analytics change disaster management by demonstrating an array of key performance indicators, mostly about data loading time, improved data quality, efficiency of response, and casualty rates. The graphs and discussions underscore the advantages of conversion into BI and faster response times and situational awareness, as well as fewer casualties. Results, therefore, provide empirical proof that such strategies in using data can and should be adopted in national frameworks for disaster preparedness.

Experimental Outcome

The data loading time by the agency is depicted in Fig 4. It captures the total time taken by different agencies in ETL of disaster-related data during a response operation. By observation, it can be said that the processing times for the ETL vary across the agencies, as the NGO Reports with the longest time while the Weather Agency and then the local emergency management department follow it. It may be due to, the complexity and massiveness of data to handle, the preparedness of the systems, level of their integration with automation in data-pipes. The need to optimize the ETL workflows has been pointed out very clearly in the chart, particularly among those that have longer loading times, as it can delay data processing and, hence, timely decision-making in a disaster. This comparison indicates the potential benefit of enhancing the efficiency of the data pipeline using automated ETL systems and coordination between agencies for effective disaster intervention and resource allocation.

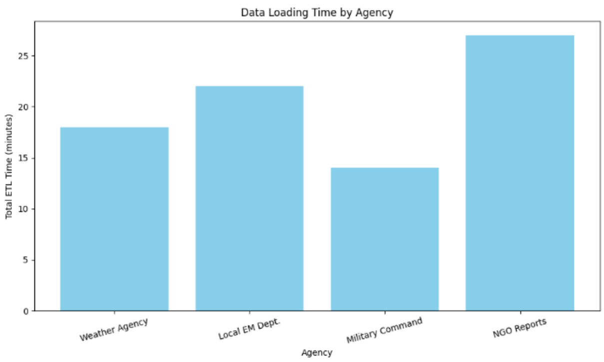

Figure 4: Data Loading

Data quality improvement has been illustrated before and after ETL in Fig 5. The extent of improvement in data quality after the ETL process amounted to much more. A bar chart exhibiting the before and after situation demonstrates that there were significant reductions in missing data, duplicate records, and errors after traversing the ETL pipeline. A sizeable improvement establishes how useful the ETL process is for cleansing unrefined data for reliable and accurate intelligence. Such improvements capably enable decision-makers to counter any disaster with high-quality accurate data, hence aiding timely and informed decision-making. The graph showcases the significance of a credible ETL lifecycle to the integrity of data used in disaster response.

Figure 5: Data Quality Improvement

The Incoming Disaster Data Volume Varied Over Time in Fig 6 is the first ten hours of cumulative collection of data after the commencement of a disaster. A steady and rapid rise of the data influx is seen in the line graph, a station on approximately 50 MB during the first hour. By the tenth hour, it grows above 1,000 MB. This form reflects the continuous change of environments in disasters where inputs are formed from different sources within a very short period as integrating media, like weather updates, field reports, satellite imagery, and emergency communications, underpin the decision-making process. A very steep rise especially between hours 3 and 7 suggests a critical period during which situational awareness heightens, requiring very well-muscled structures to absorb and process this surge. This pattern evokes the relevance of scalable ETL systems and real-time BI tools able to process high data volumes within tight temporal conditions for accurate and timely probe responses.

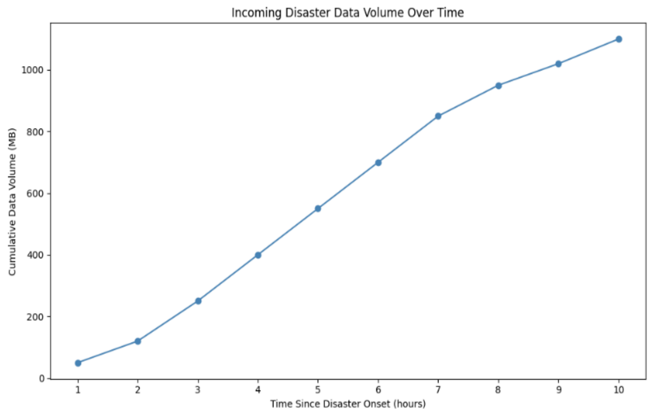

Figure 6: Incoming Disaster Data

BI has led to an increased decrease in response times for major operational agencies shown in Fig 7. The bar graph compares average response times for the medical, rescue, logistics, and coordination units before and after the implementation of BI. Before the new BI was applied to the organization, there was a very long time from 60 minutes for a medical team to 120 minutes for a logistics team. After the BI was implemented, all units had almost 50% less time, i.e., logistics went from 120 minutes to 60 minutes, rescue from 50 minutes, and coordination now takes 40 minutes. This enhancement expresses the operational efficacy gained by BI tools with real-time information, predictive analysis, and single dashboards to fast-track decision-making and resource deployment. The graph thereby is emphatic on the core of BI towards avoiding delays, improving coordination, and saving lives by response.

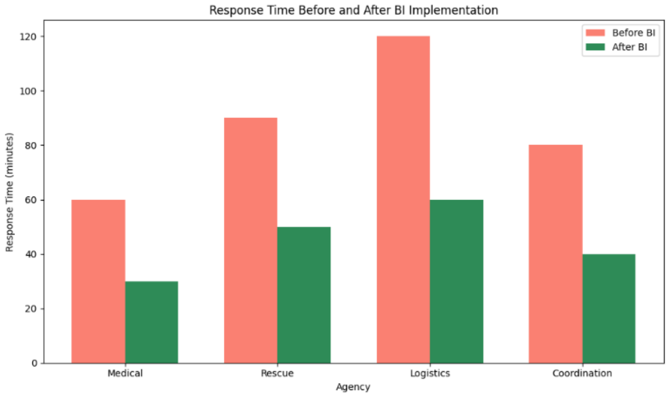

Figure 7: Response Time

The Casualty Rates Over Time With and Without BI in Fig 8 neither reveal the major role of Business Intelligence (BI). The graph of cumulative casualties over 10 hours after the onset of disasters demonstrates a huge difference between responses with BI and without BI. The casualties without BI spike to almost about 500 by the tenth hour; whereas, with BI, the casualty rate rises at a slower, more controlled pace, plateauing at just over 300. The numbers reflect how BI facilitates faster decision-making, better resource allocation, and proactive response strategies by providing real-time situation awareness and predictive analytics. The graph reveals, therefore, that BI is efficient, as it straightly saves lives by enabling agencies to act the minute every second counts in disaster scenarios.

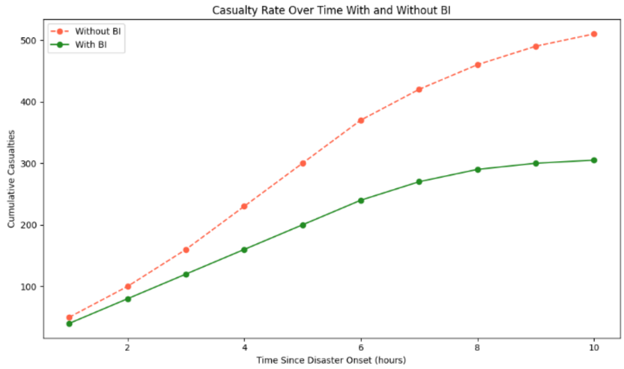

Figure 8: Casualty Rate Over Time

A comparative analysis of our MLP-LSTM model and existing methods such as CNN and SVM will be discussed in Table 1. The result indicates that the MLP-LSTM approach outperformed others across all major evaluation metrics. In comparing CNN, a recall of 96.77% and precision of 91.5% would be considered high; however, accuracy stood at the low end of 74.8% with an F1-score of 88.52% down-concurring (meaning one or the other might have been compromised along the way due to false positives or model generalization). The SVM model, on the other hand, performed overall better; while having very strong accuracy plus 95.56%, its precision and recall are in reasonable balance. However, the proposed MLP-LSTM architecture was found to beat them, scoring recognition with a whopping 99.32% accuracy, 98.72% precision, 98.77% recall, and 98.12% F1. This underpins the effectiveness of MLP-based feature extraction combined with LSTM's temporal learning capabilities for more reliable and accurate predictions of disaster-related variables, hence facilitating the timely decision-making process in such vital scenarios.

Table 1: Comparison with Existing Methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN [21]	74.8	91.5	96.77	88.52
SVM [21]	95.56	93.3	95.66	95.32
Proposed MLP-LSTM	99.32	98.72	98.77	98.12

5. Conclusion and Future Work

Disaster preparation is firmly grounded in ETL and BI technology collaboration for military-civilian response collaboration, thereby enhancing the responsiveness of any national response capacity. ETL eases data collection and standardization from many sources: weather agencies, emergency services, NGOs, and military reports. This data is combined and creates an avowed foundation for BI systems generating useful information from real-time situational awareness to predictive modeling and post-disaster analytics. Dynamic dashboards interfaced to provide visual reports and trends create faster and easily actionable BI information for decision-makers in various agencies regarding rapid-going changes in disaster situations. Historical scenarios like Hurricane Katrina in the US highlight the detrimental effects of poor coordination and fragmented data—one situation that could have greatly benefited from the presence of ETL and BI systems. The integration of these systems fosters common operational awareness between civilian and military elements while breaking down the data silos toward a synchronized, data-driven approach for resource allocation, evacuation planning, and recovery. Heading for shorter response times, fewer casualties, and better operational coordination are the benefits that witness how intelligent handling of data can transform disaster contingencies.

Future work will address AI-based data quality checks for the automation of ETL pipelines. This activity will extend the BI systems to acquire real-time sensor data from IoT, UAV image feeds, and social media. The next research effort must explore decentralized BI platforms where local agencies can work autonomously while contributing to the national disaster intelligence network. Significant areas for standardization across jurisdictions and system interoperability should be a focus for any forthcoming framework for worldwide disaster cooperation. Finally, machine learning would complement BI dashboards with enhanced predictive ability for assessing the impacts of disasters. These future trajectories aim to turn disaster management into an agile, resilient, and intelligent domain.

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