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A SYSTEM ARCHITECTURE FOR DISASTER MANAGEMENT SYSTEM

Abstract

In the era of accelerating climate change and growing urban populations, the frequency and severity of natural disasters have increased significantly, posing substantial threats to infrastructure, economic stability, and human lives. Disasters, including the likes of earthquakes, floods, and hurricanes usually are the reasons for serious destruction of buildings, requiring rapid and accurate assessment to aid in emergency response and resource allocation. In light of this, the research aims to deliver a deep learning based building damage assessment model, which is a hybrid architecture consisting of Artificial Intelligence and IOT. In this paper we will examine the use of Internet of Things (IoT) and Artificial Intelligence in disaster management systems in order to improve the automation, transparency, and sustainability in smart intelligence systems. The system should collect and analyze pre-disaster and post-disaster aerial imagery to classify buildings into damage categories, i.e. from no damage to destroyed.. Also, we integrate our model into a wide disaster management system in order to make a visualization of damages on a geospatial interface, that helps the decision-makers to get a quick look at priority areas and streamline the response of disaster. This system's plan is to assist public authorities, NGOs, and first responders with quick decision making in post-disaster response times.

Keywords: disaster management, damage detection, natural disasters, system architecture, middleware, AI, IoT.

Introduction

Unforeseen disasters, including earthquakes, storms, floods, and wildfires, are constantly damaging urban centers worldwide, causing serious destruction to buildings and endangering many lives, and infrastructure. According to data from Our World in Data, between 2010 and 2022, the most significant contributors to economic damage from natural disasters as a share of GDP–were storms, earthquakes, and floods [2]. At the same time, the highest disaster-related death rates were caused by earthquakes, floods, and extreme temperatures [1]. These statistics highlight that while storms and high temperatures have notable impacts, earthquakes consistently rank among the top causes of both economic loss and human fatalities. Given their combined impact on infrastructure and human life, earthquakes are a critical area for focused research and technological intervention.

Therefore, this paper prioritizes earthquake-related disasters when developing and evaluating the proposed building damage assessment model. In 2010, January 12, an earthquake with magnitude 7.0 brought estimated 220,000+ casualties, 300,000+ injuries and massive destruction in the capital, Port-au-Prince [3]. This is mainly due to a combination of poor infrastructure, high population density, and lack of disaster preparedness. Many buildings in Port-au-Prince were poorly constructed and could not withstand seismic activity, leading to widespread collapse and entrapment [3]. Additionally, emergency services were overwhelmed and under resourced, slowing rescue efforts and medical aid. Effective disaster management systems could have significantly reduced casualties by enforcing safer building codes, providing early warnings, training local emergency responders, and establishing clear evacuation and response plans. Investing in disaster preparedness before the earthquake could have saved thousands of lives. By using satellite or drone imagery combined with AI and machine learning, we could assess building conditions, detect structural weaknesses, and map high-risk areas. In the aftermath of the earthquake, such a system could also assist in quickly assessing damage, locating collapsed buildings, and guiding search-and-rescue teams to the hardest-hit areas, ultimately saving more lives and improving the efficiency of relief operations [19].

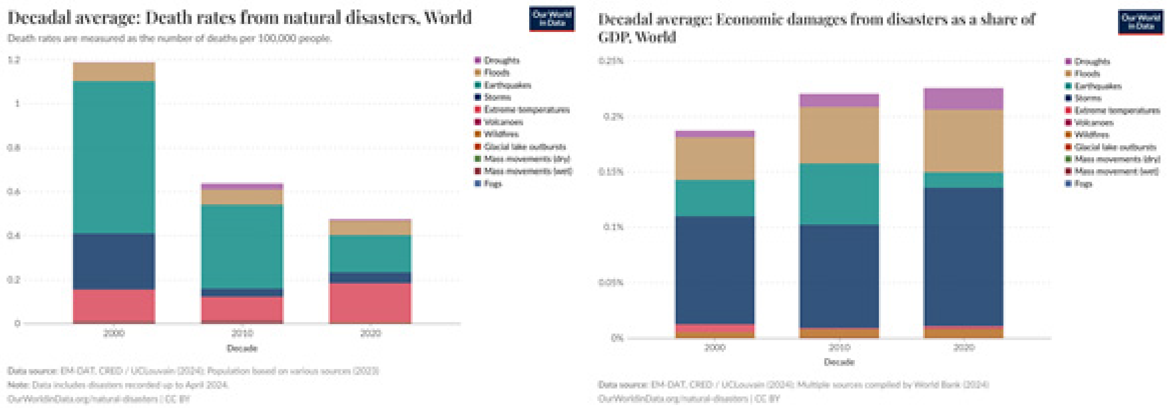

Figure 1 – Death rates and economic damage from disasters

"Disaster Information Management System (DIMS): a mechanism for effectively processing, organizing, storing and disseminating information required for disaster response and recovery, particularly in the immediate aftermath of a natural disaster event". After the aerial photos of the sites are collected, the damaged site needs to be compared to the site at the beginning of the disaster to be able to assess damage. The Disaster Damage Map can be created with aerial photos before and right after a natural disaster that shows the affected areas. This feature in the system provides initial damage assessments thus helping prioritize search and rescue operations. Moreover, another use of it is to query building damages that happened because of the accident [4].

Materials and methods

Disaster management is commonly divided into four key stages–preparedness, response, recovery, and mitigation–each of which can be significantly enhanced by using IoT technologies [5]. The preparedness stage covers the technical issues of the readiness of measures to be taken before a calamity occurs. This is where the Internet of Things (IoT) comes in to enable continuous environmental monitoring, real-time risk assessment, and effective resource allocation. Networks of sensors, cameras, and other devices give scientists the data necessary to catch early warning signs and inform the population. For example, IoT based weather stations have displayed variables that might indicate dangerous weather, giving people enough time to prepare. In the event of disaster happening, the response phase, comes into play, which is about doing coordinated and quick actions to lower the harm. IoT is beneficial to this stage by providing the channels for quick communication between first responders, increasing situation awareness and directing the overall deployment of search and rescue operations. Drones with IoT sensors can make a rapid map of the affected areas, estimate the damage of the structures, and point the routes where rescue teams can navigate. Wearable devices also help to protect the responders due to their ability to track responders' health metrics and locations in real time [21]. Then, the recovery stage focuses on normalizing the things and redoing the damaged infrastructure. Here, the role of the IoT is to promote recovery via the efficient damage assessment process and identifying rebuilding priorities. For example, IoT-enabled structural sensors can transmit safety data to central systems, helping officials prioritize which buildings require urgent repair. Smart grids integrated with IoT systems can also speed up energy restoration, ensuring essential services return more quickly. Finally, the mitigation and prevention stage seeks to reduce the severity of future disasters. IoT contributes by collecting and analyzing data from all phases of a disaster, improving forecasting models and guiding infrastructure improvements [5, 18].

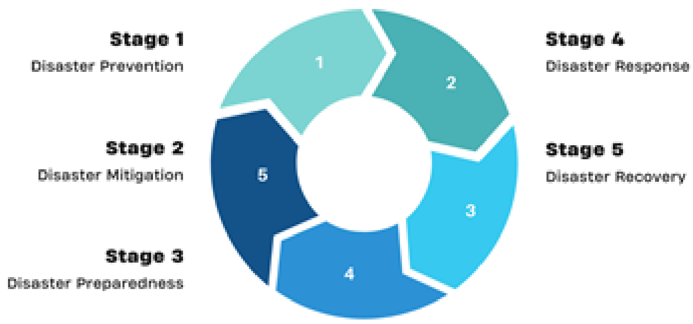

Figure 2 – Disaster management cycle

In Middleware for Internet of Things: A Survey, the authors define IoT as a network of uniquely addressable objects interconnected through standard protocols and examine its key characteristics from both infrastructure and application perspectives. The architecture we are proposing encompasses both functional and non-functional requirements listed by Mohammad Abdur Razzaque in his work. The representation of the functional part, for instance, requires that middleware facilities must, without human intervention, auto-discover resources and manage resources in the most efficient way by ensuring resource optimality. It also must apply data management tasks like obtaining, filtering and aggregating, while event management that codes raw signals into useful events and enables real-time troubleshooting for analysis. In terms of non-functional requirements, the model emphasizes scalability, allowing the system to handle increasing numbers of devices through techniques such as loose coupling and virtualization. Real-time performance is equally vital, assuring the on-time delivery of services. Reliability and availability are depicted as the critical measures to perform consistently and fast recovery in case of failure [17].

We want to present a system where AI components are integrated with data sources and IoT devices. Swarna Kamal Paul in his paper called “Disaster Management through Integrative AI” demonstrates an innovative framework that combines artificial intelligence, Internet of Things (IoT) devices, and data services into a unified platform [6]. The main idea is that the disaster management architecture should be a module, scalable, and interoperable. This is achieved by an integrative AI platform built on a dataflow graph-based programming model, supported by middleware, and connected to microservices that represent IoT devices, AI services, and data sources. The programming model is particularly significant, as it reduces the complexity of developing disaster management applications. By representing applications as directed acyclic graphs where nodes signify functions and edges represent dataflows, the system allows modularity and parallelization. This approach makes programming less syntactically demanding for users while enabling sophisticated application logic. The middleware layer that positions the API gateway handles communication is the core of the system. It takes responsibility for the routing between the program interpreter and the external services, the unification of the data formats, and the prevention of security threats through access control. This middleware supports both synchronous and asynchronous communication, ensuring that real-time disaster data from IoT devices and AI models can be processed without bottlenecks [6].

Benssam A. (2017) presents middleware which targets decision support improvement in a disaster management environment specifically. This research stands on the idea that disaster management depends on highly heterogeneous systems, ranging from sensor networks and IoT devices to existing databases and communication services. This middleware is a unifying layer that brings coherence among these different components, thus allowing data to be collected, shared, and processed without any issues. The research question contemplated by this study essentially revolves around whether middleware can improve decision-making in disaster scenarios by bridging the gap between the distributed data sources and the more sophisticated decision-making systems. It is stated that decision-making based on real-time information in critical situations depends not only on the data reliability but also on the architecture that supports timely processing and communication. In a broader perspective, middleware is a bridge connecting distributed data and real-time analysis and is also a tool for system interoperability and adaptive responses. From the results, it has been determined that middleware platforms are in fact effective in regulating the data paths and easing the system heterogeneity through the use of standardized APIs and protocols. The benefits gained in this way should be noted, as the system will share information more quickly and make decisions more swiftly, thus, reducing the time pressure that is normally present in disasters [7].

Work of Pillai. A, focus on building reliable early warning systems (EWS) by studying service-oriented IoT architecture for disaster preparedness and forecasting. The point that separates it from the traditional EWS methods is that the system is based on a layered IoT architecture integrated with a triple modular redundancy (TMR) fault-tolerant mechanism, which ensures the reliability and the absence of faulty sensor data for accurate cloud-based predictions. The paper notes the increasing importance of real-time monitoring and decision support systems in reducing risks and mitigating the socio-economic impacts of disasters, particularly in critical environments like underground mines. The main research question addressed by the paper is how IoT-based service architectures, combined with cloud-driven machine learning models, can provide accurate, fault-tolerant, and real-time disaster prediction capabilities. The authors seek to improve upon existing EWS frameworks by embedding redundancy in sensor networks and integrating machine learning algorithms for predictive analytics. The contributions of the study are demonstrated through the design of a layered IoT architecture composed of perception, middleware, service, and interface layers, which together streamline communication between sensing devices and cloud-based systems. To check the correctness of the framework the research paper analyzed the case of its utilization in underground mines, where reliable and continual environmental monitoring is of utmost importance for the provision of safety to workers and preventing hazardous conditions. The prime outcome suggests that the proposed system is able to generate highly accurate predictions even if its partial sensor fails. The combined work of lightweight IoT communication protocols, fault-tolerant sensor integration, and cloud-based predictive analytics presents a solid means of ensuring non-stop and accurate disaster prediction. This feature renders the system particularly appropriate for safety-critical sectors where downtime or erroneous data can have disastrous effects [8].

Correspondingly, the papers reveal a common aim in overcoming fragmentation in disaster management systems and enabling faster and more reliable decision-making. First paper highlights the role of AI-enhanced microservices for predictive and adaptive responses, while Benssam emphasizes the middleware's ability to harmonize diverse data sources and ensure robust communication. And the IoT architecture study highlights fault-tolerance and predictive accuracy in early warning systems. All these work acknowledge persistent problems such as real-time data constraints, scalability under high load, and the need for security in handling sensitive information. Their findings converge on the idea that middleware, whether AI-enhanced or designed as a decision-support hub, is indispensable in bridging the gap between distributed technologies and effective disaster management practices [6–8].

Artificial intelligence (AI) has emerged as a transformative tool in disaster management, offering advanced capabilities for monitoring, prediction, response, and recovery. It offers an innovative solution that integrates knowledge from diverse data types and sources, enables the simulation of realistic disaster scenarios, and detects emerging patterns with unprecedented speed. The following literature review examines key approaches and applications of AI in disaster management, emphasizing their effectiveness, challenges, and potential for improving resilience [20].

The formula behind convolution operation in convolutional neural network for multi-class classification is:

$$Y(i,j) = \sum_{m=1}^{k_h}\sum_{n=1}^{k_w}\sum_{c=1}^{C} X(i+m, j+n, c) * K(m,n,c) + b$$

Where, input image $X \epsilon R^{H*W*C}$, with height H, width W, channels C, and $Y(i,j)$ is a feature map value at location (i,j), with bias b.

Activation function is: (ReLU) is $A(i,j) = \max(0, Y(i,j))$, which introduces non-linearity.

And in order to reduce spatial size and capture dominant features, for a pooling window of pxp, the max pooling layer formula is:

$$P(i,j) = max_{(m,n)\epsilon pxp} A(i+m, j+n)$$

The formula for Adam optimizer, which will be later used for building damage classification task is follows, gradient at step t is $g_t = \nabla_\theta L(\theta_t)$, where θ_t is model parameters at step t, and L is the loss function. From there exponential moving average of the gradient would as follows: $m_t = B_1 m_{t-1} + (1 - B_1) g_t$, where m_t is biased first momentum, while the second momentum estimate is: $v_t = B_2 v_{t-1} + (1 - B_2) g_t^2$.

And the parameter update rule is given by:

$$\theta_{t+1} + \theta_t - n * \frac{m_t}{\sqrt{v_t + \epsilon}}$$

Table 1 – Building damage classification CNN models

Reference	Model	Dataset/ city	Metric	Accuracy	Size of image	Number of epoch / batch size	Building features
[9]	U-Net, ResNet	Inria Dataset, America	Dice metric Test	97.95 %	(512×512)	200	shapes, structures, textures, and colours
[10]	UNet, ResNet	Xinxing County, China	Accuracy	84.9 %	(900 × 900) to (1024 × 1024)	50 / 2	detecting new, old buildings
[11]	U-Net, ResNet50	Boston	IoU accuracy	82.2 %	(1500×1500)	60	residential buildings in urban settings
[12]	U-Net, ResNet V2	Chicago dataset	F1 score	86 %	(5000 x 5000) cut to (512 x 512)	50 / 4	shadow, man-made non-building features, heterogeneity of roof
[13]	U-Net, ResNet34	Nashik, Maharastra	Accuracy	89 %	(512 x 512)	25 / 16	residential, industrial, holy places
[14]	U-Net, ResNet34	SpaceNet	Accuracy	84.7 %	(650 × 650)		building footprint extraction

Recent literature on CNN-based building damage classification consistently shows that encoder–decoder segmentation architectures, most commonly U-Net paired with ResNet backbones, are effective for extracting building footprints and diagnosing damage from high-resolution aerial and satellite imagery [15, 16]. Across diverse datasets such as Inria, SpaceNet, and city-scale datasets such as Boston, Chicago, Xinxing County, and Nashik, these hybrid models benefit from the strong feature-extraction capacity of ResNet variants and the spatial-precision of U-Net decoders. Reported performance varies by dataset and task metric, ranging from very high Dice scores on clean building-extraction tasks (≈97.9% on Inria) to more modest IoU/F1 results (≈82–86%) in urban settings where roof heterogeneity, shadows, and surrounding man-made features complicate segmentation. Differences in image resolution, pre-processing, and experimental setup strongly influence outcomes. Studies using large original tiles (e.g., 1500×1500 or 5000×5000) that are cropped to smaller patches (commonly 512×512) enable models to learn both contextual and fine-grained cues; however, varying patch sizes and batch/epoch regimes (examples: 200 epochs at 512×512 vs. 50 epochs with batch size 2 at 900–1024 tiles) make direct comparison difficult. Performance also depends on the target labeling: tasks focused on building footprint extraction tend to report higher segmentation metrics, whereas damage classification, especially distinguishing new vs. old or partially damaged buildings, suffers from lower recall/F1 because the visual cues of damage are subtle and dataset imbalance is common [9–14].

Common challenges and recommended directions emerge from these works. First, data heterogeneity between different cities, roof materials, shadows, and non-building objects requires robust augmentation, domain adaptation, or fine-tuning strategies to transfer models between regions. Second, combining spectral, temporal (pre/post-disaster) and contextual metadata often improves damage detection beyond single-image segmentation.

Results and discussion

Building on the insights from existing research, the proposed system architecture is designed to address the challenges of fragmentation, real-time data processing, scalability, and security in disaster management. It is an integrated, AI-driven platform that analyzes pre-disaster and post-disaster imagery to assess structural damage in buildings following an earthquake. This system architecture could be described as modular, cloud-native, and it is organized around microservices to provide flexibility, fault tolerance, and ease of deployment. The pivotal component of the whole system is the Data Ingestion Layer, which aggregates data from lots of sources, such as satellite and drone images, IoT sensor data from in-situ devices, and historical building records. This layer facilitates both batch and real-time data collection through secure APIs and automated upload pipelines. After collection, the data enters the Middleware and Communication Layer, which operates as the platform's central nervous system. Here, the Middleware using Kafka or RabbitMQ integrates message queues and event brokers to transform the data, adapt formatting, and ensure proper, asynchronous module communication, which thus, upon dealing with integration gaps specified in the literature, facilitates the whole process [17]. The AI and ML layer is the system intelligence hub. It has a collection of microservices, which are containerized and can be updated independently. They perform tasks such as building detection, comparing pre- and post-event images, and deep learning models for damage classification. These models are fine-tuned for speed and reliability, supporting both real-time inference and batch processing after the incident.

The Decision Support Layer, for example, gets the outputs from this layer and it is here that the various outputs such as damage scores, heatmaps, and risk assessments that are generated and presented through a web dashboard. The dashboard was created specifically for emergency response teams with visual tools and prioritization recommendations to help them during rapid and informed decision-making. The entire architecture is underpinned by the Storage and Data Management Layer, which is solid and robust. It makes use of distributed object storage for high-resolution images and structured databases like PostgreSQL for metadata and model outputs. Data versioning, indexing, and lineage tracking are implemented to ensure auditability and traceability which are key requirements in disaster scenarios. To prevent breaches of sensitive information, the system incorporates a Security and Access Control Layer that implements role-based access, encrypts data both at rest and during transit, while also maintaining comprehensive audit logs for accountability. The system, in the end, is built not only for scalability but also for fault tolerance. This is achieved by each microservice being horizontally scalable which enables the system to burst during high traffic moments under a natural disaster. Health checks, load balancing, and redundancy mechanisms will keep the system working even though not all parts are functioning correctly. Simply, all these architectural decisions are behind a strong, intelligent, and capable platform that can deliver timely and reliable post-earthquake building damage assessments.

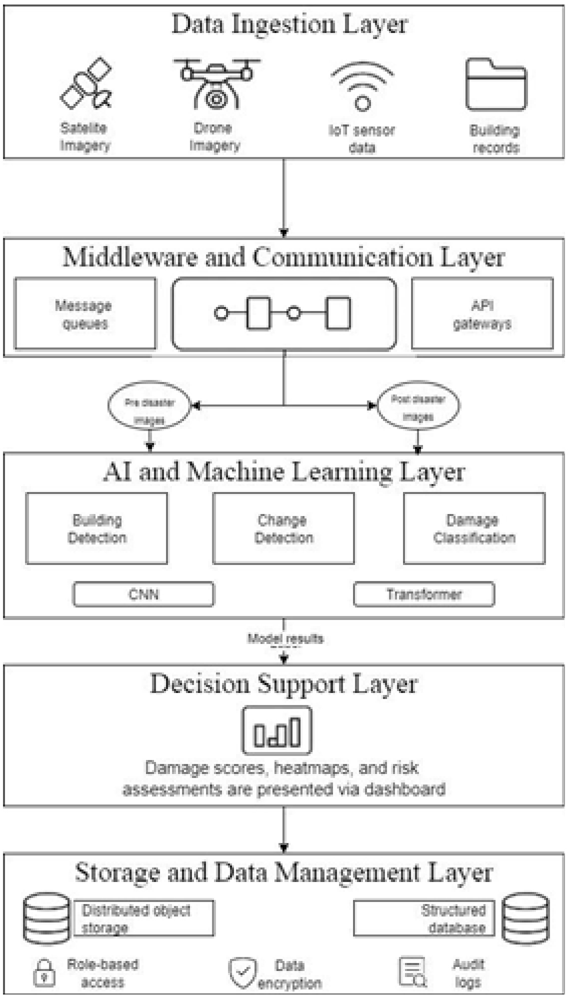

Figure 3 – Proposed system architecture

To evaluate the effectiveness of the proposed architecture, we implemented and tested the AI-based damage classification component, which plays a central role in the system's analytical layer. This component would be integrated within the broader microservices framework described earlier, enabling seamless data flow from ingestion to analysis and visualization. Approach for building damage assessment using satellite imagery is to pose the problem as a combination of segmentation and classification tasks and to train deep-learning models on pre-disaster and post-disaster satellite images. The problem of damage classification can be thought of as a change detection problem, where the change is to be calculated over a period of time with a pair of pre- and post-disaster images [22]. The model was trained using the xBD dataset by Maxar and Microsoft AI for Earth is a large-scale satellite imagery dataset for building damage assessment, containing pre- and post-disaster imagery with building footprint annotations and damage classifications (No Damage, Minor, Major, Destroyed). The method of identifying damage level is that the model firstly represents a particular building as a polygon and assigns a damage class to the polygon by comparing the difference between polygon representation of pre- and post-disaster satellite imagery.

Figure 4 – Satellite imagery and polygon representation

This CNN architecture is designed for 4-class building damage classification. It begins with three convolutional blocks (Conv2D → MaxPooling → BatchNorm), progressively reducing spatial dimensions while increasing feature depth. The output is flattened and passed through a dense layer with 128 units, followed by dropout for regularization. Finally, a dense output layer with 4 units predicts the damage class. The subsequent part enumerates the performance statistics of the building damage classification model, underscoring its precision, trustworthiness, and realistic utility in post-earthquake scenarios. These findings also provide information on the effectiveness of the system in actual circumstances thereby serving to prove the practicability of the use of AI in decision support within the system. The training and validation accuracy curves in the top plot show that the CNN model consistently achieves around 75.5% accuracy, with little improvement over 30 epochs, indicating early convergence. Meanwhile, the loss curves in the bottom plot demonstrate that training loss steadily decreases, while validation loss fluctuates, suggesting that the model may be overfitting slightly or struggling to generalize, especially due to class imbalance.

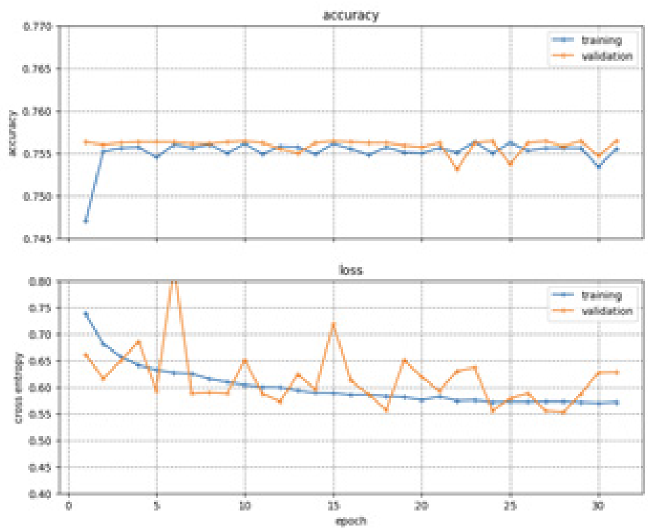

Figure 5 – Accuracy and loss function graph

Table 2 – Confusion matrix

	precision	recall	f1 score	support
class 0	0.76	1.00	0.86	6935
class 1	0.31	0.06	0.10	514
class 2	0.5	0.02	0.04	1675
accuracy			0.77	9124
macro avg	0.52	0.36	0.33	9124
weighted avg	0.68	0.77	0.67	9124

The matrix shows that the model is biased toward class 0, which dominates the dataset. Class 0 achieves strong performance with a precision of 0.76, perfect recall of 1.00, and an F1 score of 0.86, indicating that almost all instances of this class are predicted correctly. In contrast, the minority classes perform poorly. Class 1 and 2 have modest precision, but a low recall, which results in a weak F1 score, meaning most true instances of this class are missed. Overall accuracy is 0.77, but this is misleading because it is mainly driven by the number of correctly classified class 0 samples. The macro average precision 0.52, recall 0.36, F1 0.33 highlight poor balance across classes. The performance on classes 1 and 2 is very likely linked to their much smaller support compared to class 0. As a result, it learns to prioritize predicting the majority class, since doing so maximizes overall accuracy.

After balancing the dataset across classes and adopting the SiamUnet model which is more effective compared to traditional sequential CNN model, we see improvements in results, as shown in table 3. The architecture of the model consists of two identical U-Net encoders and decoders that process the pre- and post-event images separately. Each branch extracts multi-scale features using convolutional and pooling layers, followed by symmetric upsampling and decoding. After individual decoding, the Siamese module computes the difference between feature maps (bottleneck_2 and bottleneck_1) to capture the extent and location of changes. These difference maps are then progressively upsampled and concatenated with encoder differences from earlier layers, enabling the network to reconstruct fine-grained change patterns. The model was trained using the Adam optimizer with a learning rate of 1e-4 and batch size of 8, training on 20 epoch. Two types of experiments were conducted:

Cross-event training: where model was trained randomly on all 19 different disaster events included in xBD dataset.

Event-specific training: where model was trained and evaluated only on images from Mexico City earthquake, following the 80/10/10 proportional split.

The results demonstrate significant improvements. It can be observed that the model performed better in classes 0 (no damage) and 2 (major damage), than in class 1 (minor damage), even though the dataset was balanced across classes. We can deduce that it might be because classes 0 and 2 have higher and more pronounced visual signs compared to minor-damaged-class. Interestingly, when the model was trained on earthquake specific dataset, classes 0 and 2 improved, whereas class 1 did not. It might be because earthquake-specific training is best at enhancing only distinctive cues, while minor damage class can be visually ambiguous, and poor satellite resolution can make it overlap with class 0.

Table 3 – F1 score for general and earthquake specific training

	Class 0	Class 1	Class 2
Metric	f1 score	f1 score	f1 score
General	0.88	0.25	0.41
Earthquake-specific	0.89	0.21	0.43

Conclusion

The proposed architecture presents a scalable, AI-driven, and cloud-native platform designed to deliver timely and reliable building damage assessments in the aftermath of earthquakes. By integrating diverse data sources, including satellite imagery, drone captures, IoT sensor readings, and historical records, the system ensures a realistic view of disaster impact. Its modular microservices design, supported by middleware for seamless communication and a robust storage layer, provides flexibility, resilience, and high performance. The inclusion of advanced AI and deep learning models enables accurate detection, classification, and visualization of structural damage. As the present work concentrates on the conceptual design of the disaster management architecture, future efforts will focus on completing the full system architecture. The next steps will involve developing the data ingestion layer to enable seamless integration of satellite/drone imagery, IoT sensor feeds, and building records. Additionally, work will extend to building the decision support layer, with an interactive dashboard that translates AI outputs into actionable insights for emergency responders. Efforts will also include establishing the storage and data management layer with distributed storage, indexing, and auditability, along with implementing the security and access control to safeguard sensitive information. Additionally, advancements in edge computing can be leveraged to bring AI inference closer to disaster sites, reducing latency and enabling offline operation in bandwidth-constrained environments.

This study demonstrated the potential of CNN-based models for building damage classification within disaster management systems. The results show that while the model performed strongly on class 0 (no damage), it struggled with classes 1 and 2. This imbalance highlights the challenges posed by unequal class distributions, where the majority class dominates training outcomes while minority classes remain underrepresented. After ensuring more balanced learning across all categories, classes 0 and 2 showed great performance, while class 1 struggled because of low visual cues and poor image quality that make it hard to capture subtle nuances of class 1. To address this, future work will focus on two main directions. First, I plan to incorporate Transformer-based architectures, which can capture richer contextual relationships and long-range dependencies, improving recognition of subtle classes. These improvements are expected to enhance the model's robustness and make it more reliable for real-world disaster management applications.

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АПАТТАРДЫ БАСҚАРУ ЖҮЙЕСІНІҢ ЖҮЙЕЛІК АРХИТЕКТУРАСЫ

Аңдатпа

Климаттың өзгеруінің жеделдеуі және қала халқының өсуі жағдайында табиғи апаттардың жиілігі мен ауырлығы айтарлықтай артып, инфрақұрылымға, экономикалық тұрақтылыққа және адам өміріне елеулі қауіп төндіруде. Жер сілкіністері, су тасқындары және дауылдар сияқты табиғи апаттар көбінесе құрылымдық зақымдануларға әкеледі, бұл төтенше жағдайларды жоюға және ресурстарды тиімді бөлуге жедел әрі дәл бағалаудың қажеттілігін арттырады. Осы сын-қатерлерге жауап ретінде бұл зерттеуде жасанды интеллект пен IoT технологияларын біріктіретін гибридті архитектураға негізделген ғимараттардың зақымдануын бағалау моделі ұсынылады. Зерттеу смарт-интеллект жүйелерінде автоматтандыруды, ашықтықты және тұрақтылықты арттыру үшін заттар интернеті мен жасанды интеллекттің кешенді интеграциясын пайдаланады. Ұсынылған жүйе апатқа дейінгі және апаттан кейінгі аэрофототүсірілімдерді жинап, талдау арқылы ғимараттардың зақымдану деңгейін «зақымданбаған» күйден бастап «толық қираған» деңгейге дейінгі санаттарға жіктейді. Сонымен қатар, модель кеңейтілген апаттарды басқару жүйесіне біріктіріліп, геокеңістіктік интерфейсте зақымдану көрсеткіштерін көрнекі түрде ұсынады. Бұл шешім қабылдаушыларға зардап шеккен аймақтарды тиімді бағалауға, басым бағыттарды айқындауға және апатқа қарсы іс-қимылдарды оңтайландыруға мүмкіндік береді. Ұсынылып отырған жүйе мемлекеттік органдарға, үкіметтік емес ұйымдарға және алғашқы көмек көрсетушілерге апаттан кейінгі жағдайларда жедел, дәлелді және уақтылы шешім қабылдауды қолдауға бағытталған.

Тірек сөздер: апаттарды басқару, зақымдануды анықтау, табиғи апаттар, жүйелік архитектура, аралық бағдарлама, ЖИ, заттардың интернеті

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СИСТЕМНАЯ АРХИТЕКТУРА ДЛЯ СИСТЕМЫ УПРАВЛЕНИЯ СТИХИЙНЫМИ БЕДСТВИЯМИ

Аннотация

В эпоху ускоряющегося изменения климата и роста городского населения частота и интенсивность стихийных бедствий значительно возросли, представляя серьезную угрозу инфраструктуре, экономической стабильности и жизни людей. Такие стихийные бедствия, как землетрясения, наводнения и ураганы, часто приводят к обширным разрушениям зданий, требуя быстрой и точной оценки для экстренного реагирования и распределения ресурсов. В ответ на эти вызовы в данной работе представлена модель оценки ущерба зданиям на основе глубокого обучения, использующая гибридную архитектуру, сочетающую искусственный интеллект и интернет вещей. Данное исследование объединяет интернет вещей и искусственный интеллект для повышения автоматизации, прозрачности и устойчивости интеллектуальных систем. Система предназначена для сбора и анализа аэрофотоснимков до и после стихийных бедствий для классификации зданий по категориям ущерба – от неповрежденных до разрушенных. Кроме того, мы интегрируем модель в более широкую систему управления стихийными бедствиями, которая визуализирует оценки ущерба в геопространственном интерфейсе, позволяя лицам, принимающим решения, определять приоритетность пострадавших районов и оптимизировать меры реагирования на стихийные бедствия. Эта система призвана помочь государственным учреждениям, неправительственным организациям и службам быстрого реагирования принимать обоснованные и своевременные решения в ситуациях после стихийных бедствий.

Ключевые слова: борьба со стихийными бедствиями, обнаружение ущерба, стихийные бедствия, системная архитектура, промежуточное программное обеспечение, ИИ, интернет вещей.

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