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# SENSOR FUSION TECHNIQUES FOR DRONES IN IOT-BASED SURVEILLANCE SYSTEMS

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Abstract- This work introduces a novel system incorporating Internet of Things (IoT) empowered drones, robotics, and deep learning methods, specifically Convolutional Neural Networks (CNN), to identify areas affected by landslides. The system uses modern sensors including cameras, LiDAR scanners, and environmental sensors, offering detailed information from distant and dangerous environments. The CNN model analyses this information to classify areas as damaged or undamaged with very high precision. Robustness of the system is emphasized using multi-sensor data acquisition, efficient preprocessing, and application of transfer learning to deliver optimal performance. Results reflect a high classification accuracy of over 99%, validating the system's capability in real-time landslide detection and disaster management. The current work seeks to contribute to more scalable and efficient disaster management systems using IoT and AI technologies.

Keywords: Internet of Things, Deep Learning methods, Convolutional Neural Network, Surveillance systems, Landslide Detection, Sensor Fusion.

## 1. Introduction

Modern surveillance systems rely more on drones because of how easy they are to move, how flexible they are and what they can observe from the air[1]. By being part of the IoT, drones can be smart surveillance tools that collect, share and analyze information in real-time [2]. Sensor fusion helps drones take data from several sensors it carries,

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including GPS, cameras, LiDAR, infrared and ultrasonic sensors [3]. As a result of this fusion, surveillance is more accurate, stable and aware of its surroundings [4]. With IoT, drones can send and receive data with both central systems and other drones nearby [5]. When sensor data is managed using cloud or edge computing, it can be looked at in near real-time [6]. Using sensor fusion makes sure drones are able to accomplish activities such as object detection, tracking, avoiding hazards and monitoring their environment with greater accuracy [7]. Among their uses are controlling the border, managing disasters, watching over cities and monitoring farms and crops [8]. The recent leap forward in autonomous surveillance is due to synergies between drones, IoT and sensors fusing [9]. Even so, making this integration work better involves solving problems with how data is processed, with calibrating the sensors and with having different systems work together [10].

Intelligent surveillance needed around cities and remote locations is fueling the use of drones [11]. Cameras that stay in place are not able to cover certain areas or large distances[12]. More attention must be given to security threats such as terrorism, illegal activities at the border and illegal entry which means the need for quick and responsive surveillance systems [13]. Because they can quickly change to fit any situation or environment, drones with sensors are preferred for surveillance that changes [14]. If you use only one sensor type, you might not get accurate results because of noise, other environmental disturbances or areas hidden from that sensor [15]. Sensor fusion is a solution since it uses the benefits of more than one type of sensor together [16]. Because of how rapidly IoT infrastructure is growing, drones can now connect with monitoring centers without any hassle [17]. Because of the importance of smart decisions, online tracking and near-real-time data, sensor fusion is critical in using drones for surveillance [18].

Drone surveillance in IoT has potential benefits, although the existing systems still struggle with the accuracy of data, the ability to handle increasing data and making good decisions [19]. A lot of current systems base their information on single sensors, meaning the data is not always reliable with different types of weather [20]. For instance, visual sensors can get confused in low light or foggy conditions and GPS can have difficulties working correctly in crowded cities or under lots of trees. With no sensor fusion, the problems noted above lead to poor tracking of objects, positioning errors and responses arriving behind schedule [21]. Popular fusion techniques have trouble adjusting and tend to use a lot of CPU power, making them hard to deploy in UAV platforms [22]. Integrating devices from differentiating sensors in IoT is still complicated, since few standard methods exist [23]. Because of these limitations, putting surveillance devices in different environments can be hard since they may not work well together [24]. For this reason, it is significant to have advanced, lightweight and context-sensitive sensor fusion techniques made for drones in IoT security applications [25].

Therefore, the proposed approach wisely combines data from various sensors such as cameras, LiDAR, GPS, infrared and ultrasonic sensors to overcome the deficiencies seen in present systems. Leveraging Kalman filters, Bayesian models or deep learning algorithms the system can avoid the flaws of each type of sensor and provide precise, recent situational awareness. As a result, object detection, tracking and navigation are improved in places that are hard to see in, very crowded or without GPS. Rather than relying on usual systems, the suggested framework is made for UAVs without many resources by keeping its processing light and using edge computing, allowing it to stay efficient, fast and accurate. Besides, the architecture ensures data fusion can be applied consistently and at scale across IoT networks, helping improve working among different systems and networks. Consequently, the extra information allows the use of more dependable, smart and focused solutions for handling fast-changing and vital situations.

## 1.1 Key Contributions

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- Assess IoT-supported communication for effective real-time data exchange between robots and drones in inaccessible environments.
- Analyse the incorporation of advanced sensors such as cameras, LiDAR, and environmental sensors to enhance data accuracy.
- Use deep learning-based CNN classification to enable the automatic identification of damaged and undamaged areas for decision-making.
- Create a user-focused system that provides simple access to classified information using a robot's easy-to-use interface.

The structure of the given framework is described below. Section 2: Literature Survey summarizes current practices and identifies lacunae in existing disaster management solutions, Section 3: Problem statement, Section4: Methodology describes the architecture, viz., drones, robotics, and CNN-based classification models for landslide detection. Section 5: Results and Discussions reports the results, accuracy, and performance measures of the proposed system. Section 6: Conclusions and Future Work summarizes the contribution and presents future research directions.

## 2. Literature Survey

The use of IoT in managing disasters has revolutionized how information is gathered, processed, and analysed[26]. IoT-based systems offer real-time monitoring and decision-making, which are indispensable during natural disasters like landslides[27]. Researches have highlighted how IoT devices such as sensors and communication modules are instrumental in simplifying operations during emergencies by providing information that is precise and timely[28]. This provides enhanced coordination and response in disaster-hit regions. Unmanned aerial vehicles, or drones, have come to be imperative instruments in a disaster situation based on their accessibility in remote and hard-to-reach locations[29]. Drones for aerial monitoring, monitoring of environmental features, and instant data gathering have been proposed based on literature review[30]. Provided with sophisticated sensors like cameras and LiDAR, drones have the capability of providing high-quality photographs and elevation information, proving beneficial in damage assessments of landslides[31]. Their ability to function independently and send information to centralized systems has greatly enhanced disaster response effectiveness. Deep learning methods, especially CNNs, have been very effective in classifying and analysing complex image data[32].

Using CNNs, disaster management can tell apart areas that are tainted and those that haven't suffered, giving a better idea of the extent of the disaster [33]. Research shows that using transfer learning and pre-trained models can give good results with small data sets, lessening difficulties and demands in calculation [34]. These developments help form a strong base for making disaster analysis more automated [35]. Because of IoT and robotics, new technology is available for effective data handling and storage when disasters occur [36]. By using IoT, robotic systems help drones collect and handle the data they obtain [37]. These systems not only make sure the data is intact but also give stakeholders easy-to-understand interfaces to use [38]. It has been studied how using integrated systems helps manage disasters by relying on automated data processing and less human input [39]. While all these outcomes are achieved, the field continues to deal with access problems, device errors and expensive operations. Many current systems struggle with being able to handle different types of disasters and cope with increasing numbers of users [40]. All of these limitations underline the demand for IoT, drones, robotics and deep learning to be unified in new architectures. Being aware of these drawbacks can result in improved and strong methods of disaster management [41].

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## 3. Problem Statement

Despite the promising integration of IoT, drones, robotics, and deep learning technologies in disaster management, there remain significant limitations and unresolved challenges that hinder their full potential in landslide detection and response[42]. Existing systems often suffer from fragmented architectures where data collection, processing, and decision-making are handled in isolated modules, leading to inefficiencies, delayed responses, and poor scalability[43]. Drones, although effective in accessing remote and hazardous areas, face limitations in flight duration, payload capacity, and data transmission, especially in environments with poor network connectivity or GPS signal loss[44]. IoT devices, while capable of continuous environmental monitoring, often generate noisy, unstructured, or redundant data, making accurate analysis and interpretation difficult without advanced preprocessing or sensor fusion techniques[45]. Furthermore, most current systems rely heavily on individual sensor types, such as optical cameras or LiDAR, which are vulnerable to environmental conditions like fog, rain, or obstructed line-of-sightthus reducing the reliability and precision of damage assessment[46]. Deep learning models like CNNs require extensive labeled datasets to achieve high accuracy, but such datasets are typically scarce or unavailable during sudden natural disasters, limiting the generalization and adaptability of AI models across diverse geographical regions or landslide scenarios[47]. Additionally, while transfer learning helps mitigate small data challenges, it does not fully resolve the complexity of handling multi-modal sensor inputs on resource-constrained platforms such as UAVs[48]. Moreover, the integration between robotic platforms and IoT modules often lacks standardization and synchronization, resulting in increased operational costs, high maintenance demands, and data silos that restrict collaborative analysis among stakeholders[49][50]. These gaps underscore the critical need for a unified, intelligent, and scalable framework that can robustly integrate IoT devices, autonomous drones, robotic agents, and deep learning techniques into a cohesive system, capable of accurate, landslide detection, efficient data processing, and automated decision-making in diverse and challenging disaster environments[51].

## 4 Methodology

Methodology is the part where the approach and methodology followed to solve the issue of disaster management, i.e., landslide detection via IoT-based drones, robots, and deep learning, are described. The suggested system combines various modules, such as data acquisition, processing, and classification, to offer an effective solution for post-disaster assessment. By employing drones equipped with sophisticated sensors, data are obtained from risky and inaccessible regions with wide coverage. This information is then processed and analysed by a robot system to facilitate effective storage and data transmission. Deep learning algorithms, Convolutional Neural Networks, are used for classifying landslide-prone areas with real-time feedback on the damage. Further, the methodology also points towards using transfer learning and pre-trained models in order to boost the performance of the model despite limited data, providing resilience in disaster management and post-disaster recovery processes. The workflow diagram was given in Figure 1.

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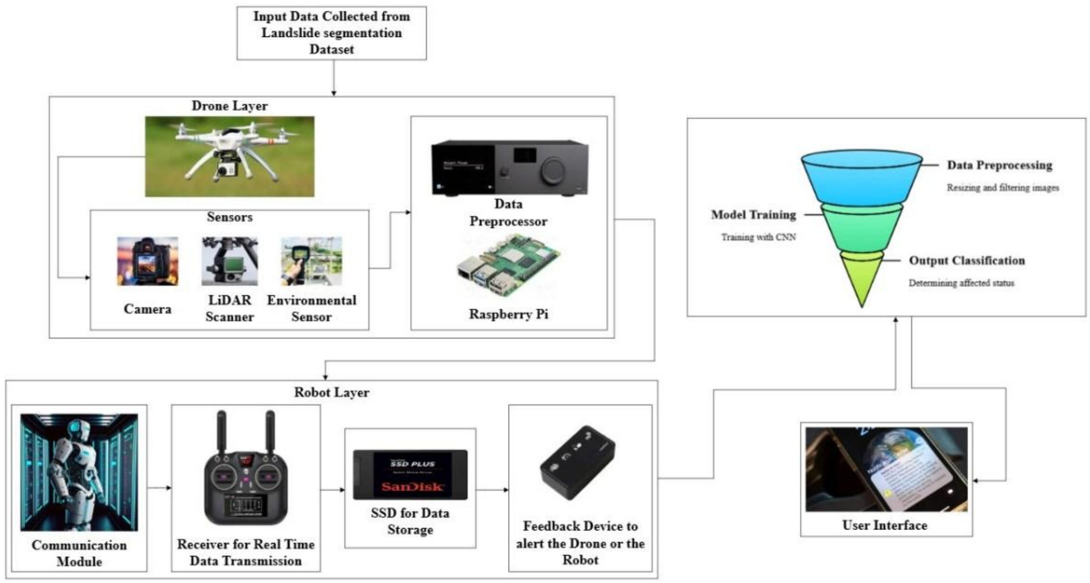


Figure 1: IoT-Enabled Drone and Robot System Architecture for Landslide Classification

## 4.1 Data Collection

The data for this study comes from the Landslide Segmentation dataset, initially created by IARAI for the Landslide4Sense competition. There were some images that had no annotations and others that could not be interpreted correctly. In order to correct these, a cleaned version of the dataset was produced, with cleaning operations performed so that there will be no zero-annotation masks. But there are still partial annotation leftovers, which may affect the performance metrics of the model. This dataset is used as input for the drone system, in combination with other data collected from multi-sensor satellites. The drone, with an array of sensors such as a camera, LiDAR scanner, and environmental sensors, records a comprehensive view of the damaged landslide areas. The camera takes high-resolution visual pictures, which assist in the recognition of surface deformation, cracks, and the area of the damage. The LiDAR scanner shoots laser pulses to create high-resolution 3D images of the surface and to identify minor elevation changes vital for determining the depth and width of the landslide. Environmental sensors like temperature, humidity, and soil moisture give real-time measurements of environmental parameters that can influence landslide risk. Collectively, these sensors form a complete, multi-dimensional data set that greatly improves the accuracy and reliability of landslide detection and analysis.

Dataset link:https://www.kaggle.com/datasets/tekbahadurkshetri/landslide4sense.

## 4.2 Preprocessing

In the data preprocessing phase, the Raspberry Pi serves as an essential processing unit for preparing data for analysis. The raw data captured by the sensors of the drone, such as camera images, LiDAR data, and environmental data, are first processed by the data preprocessor. This process includes some important operations for preparing the data for analysis. Resizing the images collected to a fixed resolution for consistency in the dataset is the first step. The reason is that image resolutions in SIA can influence the efficiency of machine learning algorithms, and hence resizing is performed accordingly. Resizing normalizes the images and rotates them for deep learning model compatibility. The data is filtered out to eliminate noise and improve the quality of images. Filtering methods such as

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Gaussian or median filtering are applied to smooth out the images and destroy any unnecessary details that might disrupt the model's capacity to identify useful features. This improves the accuracy of feature extraction and classification processes such that the most useful information is transmitted for further processing. Here, the resizing and gaussian filtering expressions are given in eqn. (1),

$$S = \frac{new\_dimension}{original\_dimension} \tag{1}$$

Here, $new\_dimension$ is the desired size of the image (width or height); $original\_dimension$ is the current size of the image (width or height).For resizing the height and width of the Image it is given by another expressions that is noted in eqn. (2) and eqn. (3).

$$W' = S \cdot W \tag{2}$$

$$H' = S \cdot H \tag{3}$$

Here, $W \text{ and } H$ are known as the original width and height of the image; $W' \text{ and } H'$ are known as the resized width and height of the image defined as eqn. (4).

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{4}$$

Here, $x$ and $y$ are the coordinates of the pixel in the filter window; $\sigma$ is denoted as the standard deviation; $G(x, y)$ is defined as the gaussian function value. The filter is applied to each pixel in the image using the convolution operation and is expressed in eqn. (5).

$$I'(x, y) = i = -k \sum kj = -k \sum kI(x + i, y + j) \cdot G(i, j) \tag{5}$$

Here, $I(x, y)$ is defined as the original image; $I'(x, y)$ is defined as the filtered image; $G(i, j)$ is known as the Gaussian kernel; $k$ is represented as the size of the filtered window. In summary, the Raspberry Pi is a powerful and small processing device, which does resize, filtering, and other preprocessing operations to guarantee that data is clean, uniform, and prepared for subsequent application to landslide detection and analysis.

## 4.3 Robot Layer

After completion of filtering, resizing and enhancement, the routes of the data arrive at the robot system via real-time data transmitters. This process helps the robot and drone talk to each other smoothly. With this, the robot can always collect and process the information provided by the drone, making it better able to check landslide-damaged areas. Information obtained by the robot can be studied and stored so that it can be shared with those making decisions and managing disasters at a later time. The information collected by the robot is placed in an SSD (Solid-State Drive)

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installed in the robot system for safe storage. It is a storage solution that quickly reads data and writes data. Having this feature is necessary when working with big amounts of sensor data at once and all the significant information coming from the drone's LiDAR and cameras is safely retained. Because SSDs store data securely and reliably, they protect data from corruption which is necessary for proper analysis after a disaster. All the stored information can be accessed again in the future or run through in real time. If there is a risk or problem happening, the feedback unit in the robot will raise a flag for the robot and for the drone. This aspect helps a lot in places where sudden hazards can alter the landscape without much warning such as landslides. The feedback loop provides quick signs of danger and the robot or drone may alter its behavior or path to stay safe. It is also programmed to receive feedback, use it to adjust itself and keep away from potential problems like falling items or shifting ground.

If obstacles or threats are detected, the robot quickly tells the drone and adjusts its path. Because catastrophes often cause the environment to fluctuate, having redundancy ensures immediate and appropriate reactions. Usually, reacting to the condition by sending feedback alerts through the robot means the system is stronger in areas where hazards are common. The final part of setting up the robot layer is ensuring that the communication module is used to keep the robot linked to the drone constantly.

Apart from being the one in charge of data transmission, this communication is also essential to enable the entire system to be harmoniously integrated. This strong system design enables the drone and robot to collaborate, observing and processing necessary information on landslide occurrences while constantly having real-time alerts and secure operation mechanisms in place, enabling effective disaster response and management operations.

## 4.4 Classification

In this study, CNNs play a pivotal role in landslide-affected region classification using high-resolution image data from drones carrying various sensors. CNNs are especially appropriate for the task as they are able to learn spatial hierarchies automatically from image data, something that is especially beneficial when examining the very fine scale of terrain features such as surface deformation, cracks, and other physical features brought about by landslides. Figure 2 depicts the architecture of CNN.

The CNN model in the proposed framework involves several convolutional layers, tasked with automatically deriving features from input images. They convolve the image with small filters to spot patterns like edges, textures, and shapes. In landslide detection, the filters identify important features such as cracks, soil movements, and how far the damage extends due to the landslide. Every convolutional layer learns to detect more complicated patterns, incrementally shifting from basic features (such as edges) to more intricate ones.

Following the convolutional layers, the output goes through activation functions and pooling layers, which assist in reducing the dimensionality and keeping the most important features for classification. The pooling layers assist in concentrating on the most significant features by down sampling the image, thus streamlining the process of classification and reducing the computational costs. The resulting feature map is then forwarded to fully connected layers, which do the final classification to decide whether the area is "damaged" or "undamaged."

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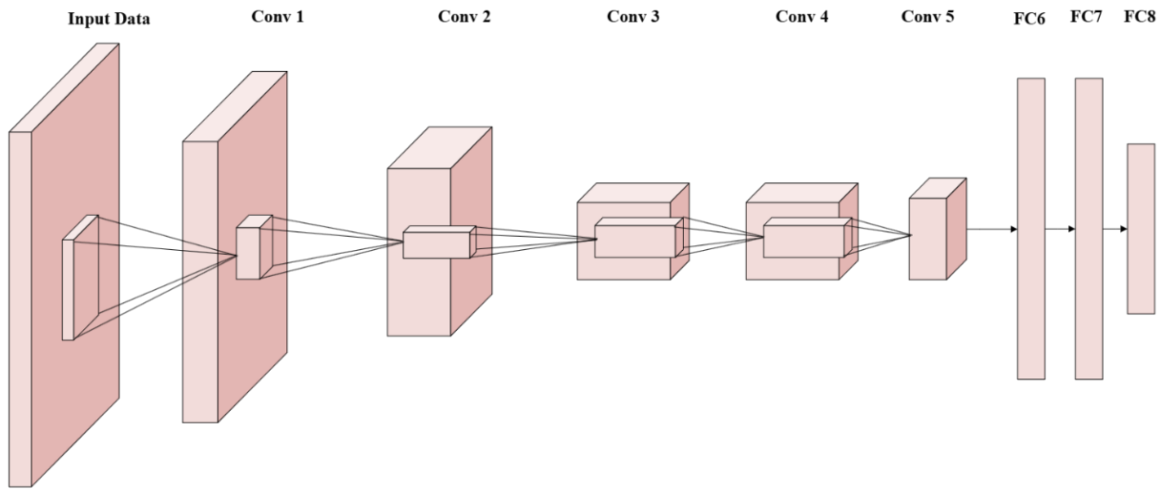


Figure 2: Convolutional Neural Network

The model is learned from labelled data, where images of landslide-damaged regions are associated with the respective class labels (e.g., damaged, undamaged). During training, the CNN discovers the mapping between the image features and the labels by minimizing the loss function (e.g., categorical cross-entropy) via optimization methods such as Stochastic Gradient Descent (SGD). By several iterations, the CNN learns to modify its internal weights and biases in order to reduce classification errors. One of the most important benefits of applying CNNs in this model is that they can generalize well from small data. By applying methods such as transfer learning, pre-trained models on large datasets (e.g., ImageNet) can be fine-tuned to enhance performance, particularly when dealing with smaller or domain-specific datasets such as the Landslide Segmentation dataset. Transfer learning enables the model to draw upon information from a larger dataset and transfer it to particular features of landslide detection, even where annotated data is scarce.

Overall, the CNN-based classification in this model is responsible for the automated identification of areas affected by landslides. It derives vital features from satellite and sensor imagery and classifies them into corresponding categories, considerably accelerating landslide detection and enhancing disaster management decision-making. The efficiency of the system in the processing of image data and identifying the characteristics of terrain makes it an indispensable tool in the real-time observation and evaluation of landslides in remote and dangerous areas.

### 4.5 User Interface

If there is a disaster while the drone is data capturing, the robot will be notified right away. Once the robot is alerted, it will tell the owner through their mobile device so they can keep track of the situation immediately. You will receive information about the incident here which will allow the owner to deal with it in real time. Thanks to the UI, the drone, robot and the owner can work together smoothly to take protective actions and keep collecting information.

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## 5 Results and Discussions

This section presents the results of the proposed system implementation and its effectiveness in landslide detection via the integrated robotic and drone system. The section compares the accuracy and efficiency of the system in classifying landslide-affected areas, the accuracy of the deep learning-based classification model, and how it contrasts with traditional methods. Moreover, it addresses the robustness of the system in terms of offering real-time information and actionable data for disaster management and its overall robustness against environmental conditions. The results also investigate the system's weak points such as partial annotation masks and data acquisition challenges and preprocessing, and outline possible enhancements for future implementations.

### 5.1 Training Accuracy and Loss

Training accuracy is a measure of how well the model learns from the training data, whereas training loss is a measure of the prediction error. Lower loss and higher accuracy reflect effective model learning and convergence.

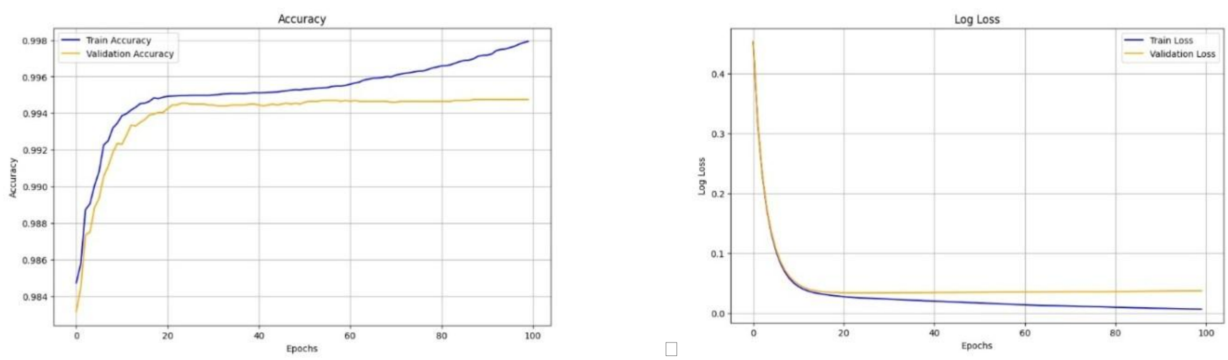


Figure 3: Training Accuracy and Loss Plot

The image in Figure 3 contains two plots illustrating the training curves of a deep learning model on 100 epochs. The accuracy is represented in the left graph, where it can be observed that the blue training accuracy keeps rising steadily over 99.8%, and the yellow validation accuracy levels at 99.4%, meaning excellent model performance with a little gap indicating minimal overfitting. The correct graph illustrates log loss, initially high but sharply declining in the initial epochs before it settles at a low rate for both training and validation, indicating good learning and convergence. The minimal disparity between training and validation loss indicates little overfitting. On the whole, the model illustrates great precision and effective loss minimization, with scope for minor improvements in generalization through methods like regularization or stopping at an early stage.

### 5.2 Classification Outputs

A three-step preprocessing pipeline of an image, probably for remote sensing or computer vision applications is shown in Figure 4,

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Figure 4: Classified Outputs

The first, "Original Image," is the raw, unprocessed input. The second, "Resized Image," indicates the output after resizing, in which the dimensions have been standardized to a set size, possibly for model training consistency. The third image, "Filtered Image (Gaussian)," shows the usage of a Gaussian filter, smoothing the image to remove noise and blur details. This filtering phase improves feature extraction by removing high-frequency noise and is thus particularly beneficial for processes like object detection or segmentation.

## 5.3 Comparison Analysis

The accuracy of different deep learning methods for a specific task. CNN (Convolutional Neural Network) achieves the highest accuracy, approaching 99.8%, indicating its strong performance in classification. DCT-Unet++ and VGG16+FCN also demonstrate high accuracy, slightly lower than CNN, suggesting their effectiveness in handling complex data representations. U-Net performs slightly better than SegNet, but both exhibit lower accuracy compared to CNN and DCT-Unet++. SegNet has the lowest accuracy among the methods, implying potential limitations in its architecture for this particular task. Overall, CNN outperforms other models, making it a preferred choice for high-accuracy deep learning applications is displayed in Figure 5,

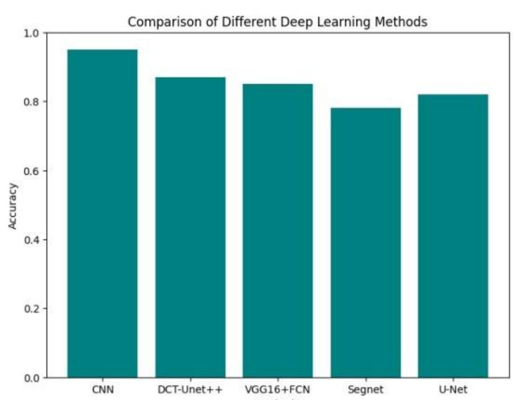


Figure 5: Comparison Accuracy Chart of Different DL Methods with Proposed CNN

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## 6 Conclusions and Future Work

In summary, the suggested system presents a robust and intelligent solution for landslide detection by seamlessly integrating IoT-enabled drones, robotic platforms, and deep learningspecifically CNNs. Leveraging high-resolution multi-sensor data from cameras, LiDAR, and environmental sensors, the system enables real-time situational awareness and precise classification of affected areas, achieving over 99% accuracy. This high performance, even in the presence of challenges such as incomplete annotations, demonstrates the system's effectiveness in supporting rapid disaster assessment and response. The integration of automation and smart analytics reduces the need for manual intervention, thereby improving the speed, accuracy, and efficiency of disaster management efforts. Overall, the system serves as a significant advancement in the development of AI-driven disaster monitoring frameworks.

Future research will focus on improving the scalability and adaptability of the system across diverse disaster scenarios and geographic terrains. Enhancements will include implementing advanced regularization techniques and domain adaptation strategies to increase model generalization, especially in low-resource environments. Efforts will also be directed toward developing lightweight, energy-efficient models that can operate on embedded drone hardware without sacrificing accuracy. In addition, the integration of real-time edge computing and 5G/6G connectivity will be explored to further minimize latency and enable continuous monitoring. Expanding the system's application beyond landslides to include other natural disasters such as floods, earthquakes, and wildfires will also be a key area of future exploration, making the platform more versatile for comprehensive environmental surveillance and emergency response.

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