



LIGHTNING PREDICTION AND ALERT SYSTEM

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ABSTRACT: Lightning, a natural phenomenon, poses substantial risks to life and property, necessitating accurate detection and timely alerts. Traditional methods relying on ground-based sensors have limitations in coverage and accuracy. However, recent advancements in deep learning have revolutionized lightning detection and alert systems. This paper introduces the Lightning Prediction and Alert System (LPAS), employing deep learning to enhance response to lightning threats. LPAS utilizes deep learning, particularly convolutional neural networks (CNNs) to process diverse data sources effectively. These models excel in detecting complex spatiotemporal patterns associated with lightning strikes. Furthermore, LPAS enables real-time lightning detection and alerting, delivering instant notifications through mobile apps, SMS, and email. In summary, the Lightning Prediction and Alert System powered by deep learning signifies a significant leap in lightning prediction technology. Its integration of multimodal data, deep learning models, and real-time alerting capabilities enhances public safety and benefits various industries. By mitigating lightning risks and enhancing our understanding of storm dynamics, LPAS promises a safer future for communities worldwide.

KEYWORDS: Convolutional Neural network, Deep learning, Remote monitoring, Alert system.

I. INTRODUCTION

A Lightning Prediction and Alert System is a crucial project designed to forecast lightning strikes, issuing timely warnings to mitigate associated risks. Lightning poses threats such as fires, electrical damage, and harm to human life, necessitating proactive measures for public safety. Utilizing advanced technology, including deep learning algorithms, this system aims to accurately predict lightning occurrences in specific areas. By integrating ground-based sensors and radar technologies, it provides real-time alerts tailored to different user groups and geographical regions. This comprehensive approach enhances community resilience and reduces the impact of thunderstorms. Detecting lightning strikes in real-time also prevents electrical damage to appliances by triggering safety mechanisms. Overall, the Lightning Prediction and Alert System serves as a vital tool for safeguarding lives, properties, and infrastructure in regions prone to lightning activity, demonstrating its significance in enhancing safety and minimizing risks associated with natural phenomena. This paper introduces the Lightning Prediction and Alert System (LPAS), employing deep learning to enhance response to lightning threats. LPAS utilizes deep learning, particularly convolutional neural networks (CNNs) to process diverse data sources effectively. These models excel in detecting complex spatiotemporal patterns associated with lightning strikes. Furthermore, LPAS enables real-time lightning detection and alerting, delivering instant notifications through mobile apps, SMS, and email. In summary, the Lightning Prediction and Alert System powered by deep learning signifies a significant leap in lightning prediction technology. Its integration of multimodal data, deep learning models, and real-time alerting capabilities enhances public safety and benefits various industries. By mitigating lightning risks and enhancing our understanding of storm dynamics.

II. LITERATURE SURVEY

Lightning Detection System Efficiency from Lightning Strike Density Analysis for Light Rail Transit

This system finds lightning detection system efficiency from ground and space as well as its correlation with lightning event counter data on existing external protection system. Lightning detection system data from ground and space in Palembang have positive correlation, even though flash rate density map from space have lower resolution than the



other one. Data from lightning event counter also have positive correlation with lightning detection system data from space. Even though they all have positive correlation, it turns out that lightning strike density from lightning event counters are 5 times higher than the space one. So, system can conclude that lightning detection system from ground absolutely have higher sensitivity and resolution than the space one.

Lightning Detection Monitoring System For Identification Transmission Line Fault in PLN Trans JBT

present evaluation of the performance lightning strike detection network on power transmission line systems. The mean, median and standard deviation of the Substation (SS) to CG vs. Fault locator distance were 2.95 km, 2.63 km and 2.70 km respectively. Since LDMS implemented in April 2017, PLN Trans JBT have optimized the use of LDMS for further inspection and maintenance improvement such as additional ground rod tower, insulator string replacement and earth wire replacement so that lightning fault trending can decrease significantly from 2016 till March 2018 (60%).

Lightning Detection and Imaging Based on VHF Radar Interferometry

In this system, detection and three-dimensional (3D) imaging of lightning plasma channels are presented using radar interferometry. Experiments were carried out in Leshan, China with a 48.2 MHz VHF radar configured with an interferometric antenna array. The typical characteristics of lightning echoes are studied in the form of amplitude, phase, and doppler spectra derived from the raw in-phase/quadrature (I/Q) data. In addition, the 3D structure of lightning channels is reconstructed using the interferometry technique. The localization results of lightning are verified with the locating results of lightning detection networks operating at VLF ranges, which indicate the feasibility of using VHF radar for lightning mapping. The interpretation of the observational results is complicated by the dendric structure of lightning channel and the overlap between passive electromagnetic radiations and return echoes.

The Adoption of IEC 62305 Standards for Lightning Protection System in Malaysia: A Success Story

This system provides an overview of the adoption of the IEC 62305 standards for lightning protection systems (LPS) in Malaysia. It outlines the need for LPS in Malaysia by providing general lightning statistics, historical changes and adoption in LPS standards. For the first time, the manuscript explains the key reasons for the success of this transition of IEC 62305, which is now being regulated by the Energy Commission of Malaysia (EC). As the Regulator for energy and gas in Malaysia, EC has successfully transformed the standards into regulations by issuing the Directive paper in 2020, taking a big leap from its initial release as a Circular in 2011. Finally, it highlights the way forward in creating a culture of self-regulation among industrial players in Malaysia.

III. SCOPE AND METHODOLOGY

Aim of the project

The primary aim of a Lightning Prediction and Alert System project are to predict lightning strikes and to issue timely alerts. By collecting data from weather stations and lightning detection systems, the system aims to analyze atmospheric conditions, historical weather patterns, and lightning data to forecast the likelihood of lightning activity. When specific criteria for potential lightning strikes are met, the system generates alerts for the benefit of the public, emergency responders, and relevant industries. These alerts are crucial for enhancing safety and enabling individuals and organizations to take preventive actions, ultimately reducing the risks associated with lightning strikes. Additionally, the system should be customizable to cater to different user groups and adaptable to various geographical regions with varying weather patterns and lightning risks.

Existing system

The current lightning monitoring and protection system works based on the intensity of the lightning based on which internal home circuit will be disconnected from external power supply line based on the raise in the voltage hike. Most of the time, it feels inefficient approach since system cant take action well in advance which results in damage of electrical equipment. While existing lightning prediction and alert systems serve important functions, they also come with several limitations. Many existing systems rely on traditional meteorological methods and simplistic algorithms for lightning prediction, which may not capture the complex dynamics of thunderstorm development accurately. This can result in limited predictive accuracy, especially in cases of rapidly evolving weather conditions. Ground-based lightning detection networks have coverage limitations, particularly in remote or sparsely populated areas. This can lead to gaps in lightning monitoring and prediction, reducing the effectiveness of alert systems in providing timely warnings to all affected regions.

Proposed system

Below Fig shows the architecture of the proposed system. System contains Four main modules called Pre-processing,



Model creation, System Training and Classification. Pre-processing module is used to pre-process the dataset images by resizing them to required dimension. Model Creation module is used to construct a machine language model using desired number of layers. System training phase is used to train the system with dataset images and store the model weight. Classification module is used to classify the input video data to determine whether it has lightning or not.

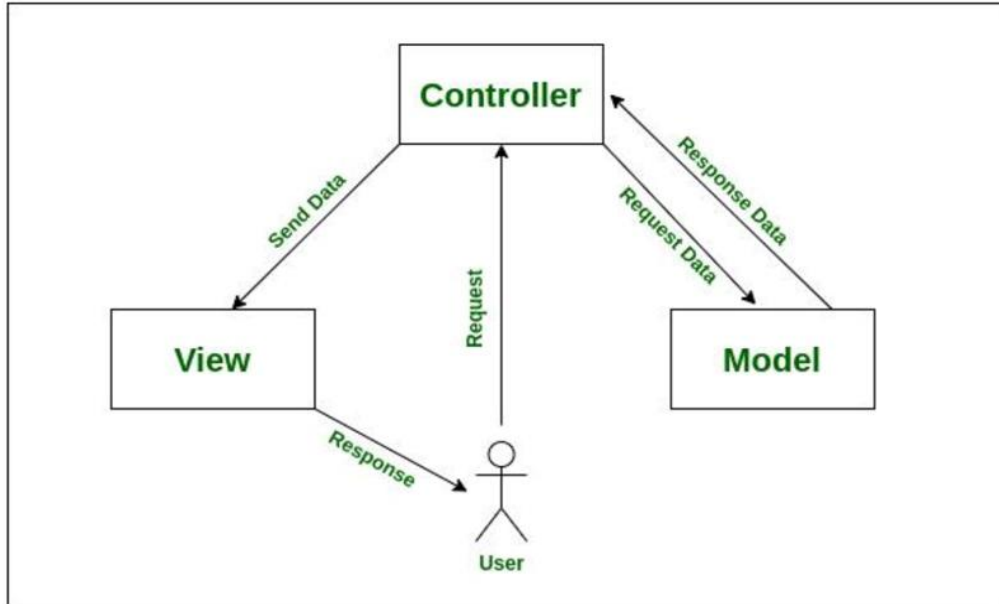


Fig 1. Proposed system

System Architecture

A formal explanation of a system is provided by an architectural explanation, which is arranged to support reasoning regarding the system's structure, individual components' properties that can be observed from the outside, and the interactions between them. It also offers a framework from which systems can be developed and products acquired that will cooperate to implement the system as a whole.

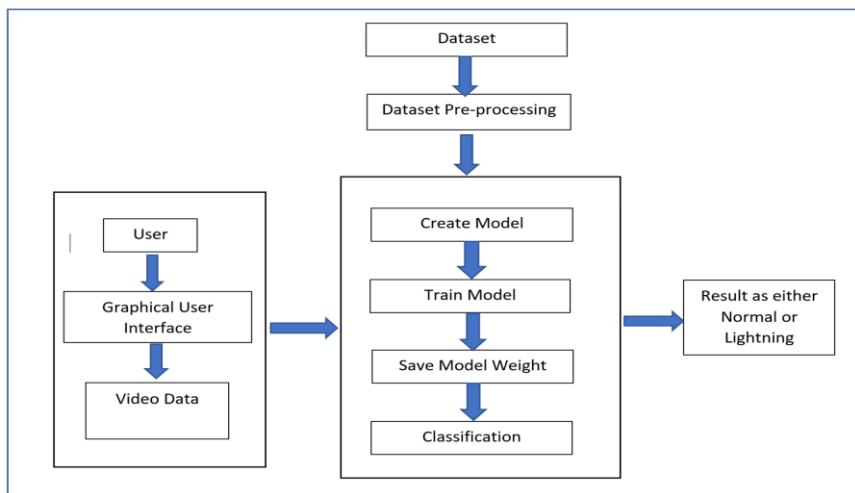


Fig 2. System Architecture

A lightning prediction and alert system operates through a network of sensors strategically positioned to detect electromagnetic signals associated with lightning strikes. These sensors collect data on the time, location, and intensity of lightning activity, which is then transmitted to a central server for processing. Through algorithms and data analysis techniques, including statistical methods and machine learning, the system generates predictive models that assess the likelihood of lightning strikes in specific regions. When a high probability of lightning activity is identified, alerts are



issued through various communication channels such as mobile apps, SMS, or email. Users can access real-time lightning data, forecasts, and alerts through a user interface, which may be web-based or available as a mobile application. Integration with external systems, such as emergency response platforms, facilitates coordinated action in response to alerts. Continuous monitoring and maintenance ensure the reliability and effectiveness of the system, with feedback loops updating prediction models based on actual lightning events. Overall, the architecture of a lightning prediction and alert system aims to minimize risks and enhance safety by providing timely warnings of impending lightning strikes.

IV. IMPLEMENTATION

System Implementation

Introduction

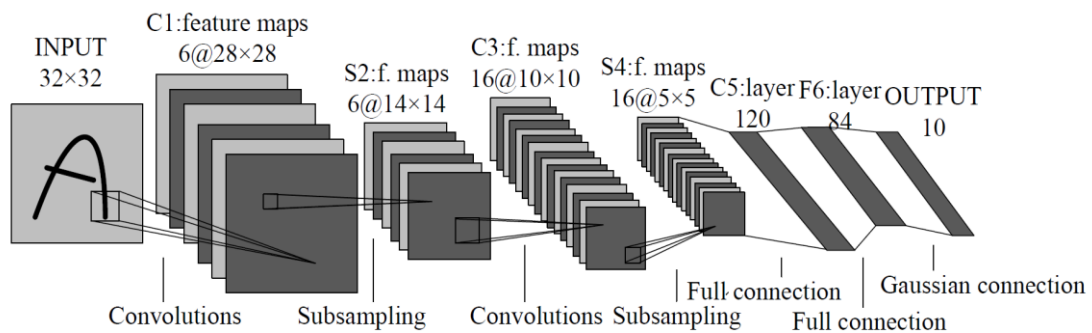
A crucial phase in the system development life cycle is successful implementation of new system design. Implementations simply mean converting new system design into operation. The term implementation has different meanings, ranging from the conversion of a basic application to a complete replacement of computer system. Implementation is used here to mean the process of converting a new or revised system design into an operational one.

Algorithm Used

The algorithms used in this project:

- Convolution Neural Network (CNN)

Convolution Neural Network



Convolutional neural network is a representative algorithm in deep learning. It is essentially a multi-layer perceptron that simulates local perception to achieve an input-to-output mapping. It extracts the characteristics of the data at different scales through multiple convolutions and pooling. What is unique in the CNN network is the way used in local connections and shared weights. On the one hand, it reduces the number of weights which makes the network easy to optimize, and on the other hand, it reduces the risk of overfitting. CNNs are generally composed of three mutually supported levels, namely convolutional layer, pooling layer, fully connected and Softmax layer. In the convolution process, we get local features. Since one of the convolution layers is composed of multiple convolution units, in the calculation process, in order to extract more features about the input parameters, it is necessary to obtain more complex feature correlation values from low-level convolutional layers through multi-level cascading.

Workflow

The following steps are carried out to implement the proposed system.

Pre-processing

Data Pre-processing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.

Dataset is pre-processed to resize the dataset images. We created our own dataset from a lightning video and created frames and images are resized to 150*150 before processing them further.

Train Test Split

The process of organizing data into groups and classes on the basis of certain characteristics is known as the classification of data. Classification helps in making comparisons among the categories of observations. It can be either according to



numerical characteristics or according to attributes. So here we need to visualize the prepared data to find whether the training data contains the correct label, which is known as a target or target attribute. In this project the dataset is split into 90 samples for training and 10 for testing.

Training

The process of training an ML model involves providing an ML algorithm (that is, the learning algorithm) with training data to learn from. The term ML model refers to the model artifact that is created by the training process. The training data must contain the correct answer, which is known as a target or target attribute. The learning algorithm finds patterns in the training data that map the input data attributes to the target (the answer that you want to predict), and it outputs an ML model that captures these patterns.

Picking the Model

Pickling is a process in which model is stored in a file for future use. Before pickling model must be trained well and optimized to maximum extent possible because after pickling model, data will not be trained. By pickling there is no need of training the model each time the user makes a classification.

Pseudo code of system

Step 1: Collect dataset

Step 2: Pre-process dataset

 Import libraries/modules

 For every image in dataset:

 Read a image from dataset using imread()

 Resize the image using resize()

 Perform Image augmentation using ImageDataGenerator()

 End for

Step 3: Build Model

 Create a CNN Model

 Add an input layer of size (150,150)

 Add convolution, pooling, dense layer

Step 4: Train Model

 Split the dataset into training set and test set in 90:10 proportion

 Configure training parameters (batch size, number of epoch)

Step 5: For I in range(epoch)

 For image in training set(X_test):

 Extract feature

 Add corresponding labels (Y_test)

 Evaluate the training accuracy and validation accuracy

 If model accuracy < 90

 Adjust model parameter

 Repeat Step 5

 Else:

 Break;

Step 6: Save model weight in .h5 file

Code implemented

The following are the code snippets used in the project.

- **Importing required packages**

```
# Importing the Keras libraries and packages
```

```
from keras.models import Sequential
```

```
from keras.layers import Conv2D
```

```
from keras.layers import MaxPooling2D
```

```
from keras.layers import Flatten
```

```
from keras.layers import Dense
```



- **Pre-processing the dataset images**

```
from keras.preprocessing.image import ImageDataGenerator
```

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True)
```

```
test_datagen = ImageDataGenerator(rescale=1./255)
```

- **Splitting Dataset and Training**

```
training_set = train_datagen.flow_from_directory('DS/train',
                                                target_size=(64, 64),
                                                batch_size=32,
                                                class_mode='binary')
```

```
test_set = test_datagen.flow_from_directory('DS/test',
                                            target_size=(64, 64),
                                            batch_size=32,
                                            class_mode='binary')
```

V. TESTING

White Box testing:

White box testing strategy deals with the internal logic and structure of the code. It is also called as glass, structural, open and clear box testing. The test that are written based on the white box testing strategy incorporate coverage of the code written, branches, statements and internal logic of the code etc. In order to implement white box testing the tester has to deal with the code and hence it is required possess knowledge of the coding and logic i.e. Internal working of the code.

Black Box testing

Black box testing takes the internal perspective of the test object to derived test cases. These tests can be functional or non-functional though usually functional. The test designer selects valid and invalid inputs and determines the correct input. There is no knowledge of the test object's internal structure. This method of test design is applicable to all levels of software testing: unit, internal, functional and system and acceptance.

Unit Testing

In computer programming, unit testing is a method by which individual units of source code, sets of one or more computer program modules together with associated control data, usage producers, are tested to determine if they are fit to use. Intuitively, one can view a unit as the smallest testable part of an application, In procedural programming a unit could be an

entire module but is more commonly an individual function or procedure. In object oriented programming a unit is often an entire interface, such as class, but could be an individual method. Unit tests are created by programmers or occasionally by white box testers during the development process

Integration Testing

The purpose of integration testing is to verify functional, performance, and reliability requirements placed on major design items. These design items, i.e. assemblages (or group of units), are exercised through their interfaces using black box testing, success and error cases being simulated via appropriate parameter and data inputs. Simulated usage of shared data



areas and inter process communication is tested and individual subsystems are exercised through their input interface. Test cases are constructed to test that all components within assemblages interact correctly, for example across producers call of procedures activation, and this is done after testing individual modules, i.e. unit testing.

System Testing

A system testing of software or hardware is testing conducted on a complete, integrated system to evaluate system's compliance with its specified requirements. System testing falls within the scope of black box testing, and such as, should require no knowledge of the inner design of the integrated software components that have successfully passed integration testing and also the software components itself integrated with any applicable hardware system(s). The purpose of integration testing is to detect any inconsistencies between software units that are integrated together (called assemblages) or between any of the assemblages and the hardware. System is more limited type of testing, it seeks to detect defects both within the inter-assemblages and also within the system as whole.

VI. RESULTS

This project integrates state-of-the-art technologies like deep learning, Python, Django, and Keras to overcome deficiencies in existing lightning prediction frameworks. Prioritizing heightened predictive accuracy, real-time monitoring, and efficient alert dissemination, LPAS emerges as a promising advancement in weather forecasting and safety protocols. LPAS aggregates diverse data sources, including historical lightning strike data, meteorological observations, satellite imagery, and environmental parameters, establishing a robust foundation for analysis.

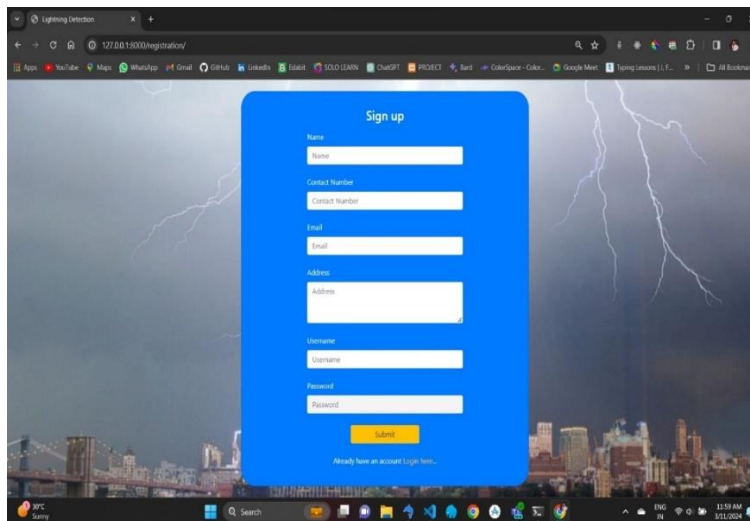


Fig 6.1 Sign up page

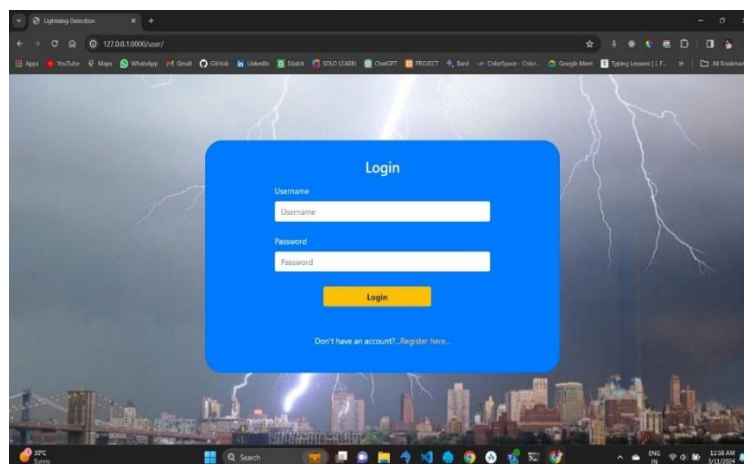


Fig 6.2 login page

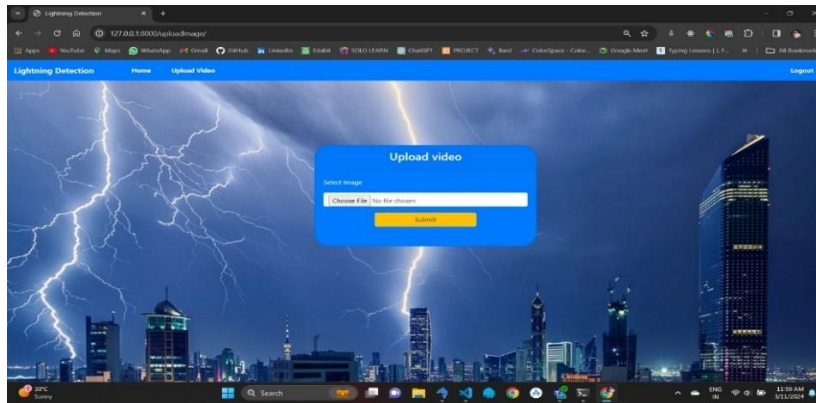


Fig 6.3 Video uploading

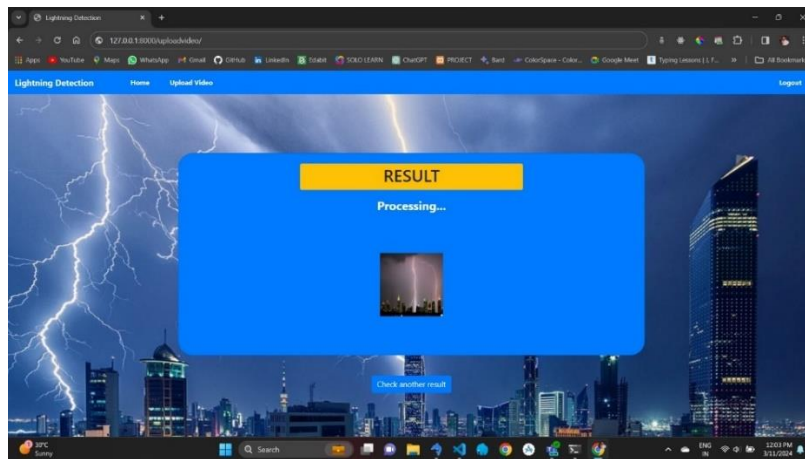


Fig 6.4 Video processing

VII. CONCLUSION

This project integrates state-of-the-art technologies like deep learning, Python, Django, and Keras to overcome deficiencies in existing lightning prediction frameworks. Prioritizing heightened predictive accuracy, real-time monitoring, and efficient alert dissemination, LPAS emerges as a promising advancement in weather forecasting and safety protocols. LPAS aggregates diverse data sources, including historical lightning strike data, meteorological observations, satellite imagery, and environmental parameters, establishing a robust foundation for analysis. Through meticulous preprocessing, the system ensures data cleanliness, normalization, and readiness for subsequent analysis. By continuously monitoring real-time data streams, LPAS employs advanced algorithms such as Convolutional Neural Networks (CNN) to accurately analyze evolving weather conditions. Its functional modules—Registration, Login, Capture Video, Train Model, Pre-process, Notification, and Classification—foster seamless user interaction and system operation. Moreover, LPAS adheres to stringent non-functional requisites, including availability, robustness, reliability, and security. Ensuring uninterrupted lightning monitoring, precise result delivery, user safety, and secure data communication, LPAS stands as a dependable solution. The provided pseudo code outlines LPAS's systematic approach from dataset collection to model training and validation, ensuring efficient deployment. LPAS holds promise as a vital tool in lightning prediction and alert systems, enhancing safety and preparedness measures for communities and stakeholders.

VIII. REFERENCES

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