Intelligent Detection of Transmission Line Hazards Using Video Image Analysis Techniques

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A new approach to power line upkeep has emerged in recent years: automated inspections driven by computer vision. In order to keep power transmission dependable, safe, and sustainable, it is now necessary to use a large collection of pictures and videos. Recent studies have shown that deep learning approaches may significantly improve power line inspection operations. Manual inspection is the gold standard for transmission line safety detection, but it's slow, susceptible to human error, and constrained by inspection cycles, ambient conditions, and the level of expertise of the inspectors doing the checks. Identifying and alerting of transmission line abnormalities in real-time is challenging, and there are substantial constraints and safety dangers to consider. A novel solution that combines the intuitive image recognition benefits of video surveillance with the high-precision range and speed measurement capacities of modern radar detection technology has just emerged: lightning fusion technology. The two datasets are intelligently merged and analyzed via the use of sophisticated data processing methods. This article delves into a lightning vision fusion–based intelligent monitoring method for transmission lines and suggests a system that uses deep learning (DL) algorithms to automatically record and analyze changes in the surrounding environment of transmission lines, greatly enhancing the accuracy and timeliness of such monitoring. In addition to reducing the need for human involvement and operating expenses, the experimental findings demonstrate that this system successfully prevents missed and false alerts, offering a stronger technical assurance for the reliable and secure functioning of the power system.

Povzetek: Nov pristop k nadzoru daljnovodov združuje računalniški vid in radar za natančno ter samodejno zaznavanje težav.

1 Introduction

A new approach to power maintenance of lines has emerged in recent years: automated inspections driven by computer vision. The use of a large database of photos and videos is now crucial for ensuring the security, longevity, and dependability of power transmission. Recent studies have shown that deep learning approaches may significantly improve power line inspection operations. Insulation materials, buildings, conductors, and fittings are just a few of the many parts that make up a power line. Power line components are prone to frequent damage due to operating in a difficult outside environment, exposed to complicated terrain and unpredictable weather. electricity outages may have far-reaching repercussions when either a single defective component, like a conductor, or a combination of several broken components, like fittings, causes electricity to go out. Catastrophic events, like forest fires, and supra-regional blackouts are both possible outcomes of these disturbances, which wreak havoc on regional power supplies. The first line of defense against such disasters is thorough examination of electricity lines. The major goal is to determine the state of the power line elements so that choices about maintenance or replacement may be made with more knowledge. Improving the efficiency of maintenance decision-making via a fast and precise inspection procedure safeguards the linked load's power supply and decreases the chance of power line breakdowns. On the other hand, power line inspection has a number of obstacles, such as traversing complicated natural settings, dealing with a wide variety of components, and covering large geographic regions. Conventional inspection techniques have used ground surveys and patrols aided by helicopters for many years. Currently, the use of machine vision and deep machine learning algorithms is revolutionizing power line maintenance. A more secure, quicker, and less expensive way to find possible problems before they become catastrophic failures is via the computerized execution of inspection procedures made possible by these technologies. Utility companies can now reliably provide energy to customers, foresee maintenance requirements, and avoid outages by utilizing high-resolution photos and real-time data processing. Nevertheless, a flood of data has been introduced by this change. In addition, the standard method for processing these media files requires laborious manual operations, which are expensive, risky, and may not provide accurate results. The power grid's ongoing expansion has led to an increase in distribution line voltage and a progressive lengthening of transmission distance. A vast network of power transmission lines must be installed in remote areas to guarantee a consistent supply of electricity throughout the nation. Forest fires may break out in the event of a prolonged dry spell or a severe rainstorm. Several studies have dealt with transmission system mountainous fire surveillance, and most investigations into transmission line fire detection have concentrated on power line equipment failures. Countless methods exist for forest authorities to detect and track the spread of mountain fires. For instance, smoke detectors are often installed in specific areas for the purpose of detection and monitoring, while weather radars and satellites are commonly used. Nevertheless, meteorological satellites have a limited resolution, which makes them susceptible to thick fog and severe weather. As a result, it becomes difficult to precisely track and detect tiny mountain fires near electricity transmission lines. Hence, the purpose of this article was to investigate transmission line mountain fire detection using picture recognition technologies. To increase the quality of the extracted picture and make it more able to detect mountain fires, we used image recognition technology to perform noise reduction, feature extraction, and image enhancement. This improved the identification speed and accuracy. Due to factors such as the striking resemblance between weeds and bird nests on transmission lines, the backdrops of distant places where transmission lines are located may be complicated. These areas frequently include high ranges and hills. In this study, we address this intriguing issue by introducing the EfficientLite network to augment the Head layer network's feature extraction. The objective is to enhance the EfficientLite network model's capacity to extract detailed information from transmission line aerial images, decrease the likelihood of false positives and missed detections, and make the model more practical and reliable for preventing transmission line disasters through safety detection. An imbalance in the samples makes it difficult to advance single-stage networks. A plethora of negative background samples are available, particularly for use in catastrophe prevention and transmission line safety detection applications. As of right now, not many academics in the subject of practical engineering have acknowledged the fact that sample imbalance does, in fact, exist.

This study is structured into the following four sections. In the second section, we survey the relevant literature on the topic of our study. In Part 3, we go over the details of how to use a deep learning algorithm and a platform built on a dual reality system to locate transmission lines. The experimental analysis of the suggested algorithm and design system is presented in the fourth section. Lastly, this report concludes with a brief summary of the key points and findings.

2 Related work

Because of their outside location, electricity transmission lines are vulnerable to a variety of threats that might compromise system dependability. One of the most popular approaches to operational and maintenance work is the integration of UAV inspection with intelligent detection technologies. Nevertheless, problems with detecting speed and accuracy continue. Through the use of scene prior information and information distillation methods, this research presents a new method for detecting components of transmission lines. The first step is to use visual analysis on high-resolution aerial photos of transmission lines. Next, the parameters of the clustering method are chosen based on the scene's previous knowledge, which allows for adaptive sub-region clustering and pattern optimization. Next, the resulting sub-regions are used as shared feature distillation masks, and knowledge distillation is utilized to transmit comprehensive image feature information obtained from the teaching model to a student network. By analyzing the dataset extensively, we can see that the suggested strategy is far more effective than competing models, with gains in accuracy ranging from 2.6% to 49.0% [12].

Manual inspection is the gold standard for transmission line safety detection, but it's slow, susceptible to human error, and constrained by inspection cycles, ambient conditions, and the level of expertise of the inspectors doing the checks. Identifying and alerting of transmission line abnormalities in real-time is challenging, and there are substantial constraints and safety dangers to consider. A novel solution that combines the intuitive image recognition benefits of video surveillance with the high-precision range and speed measurement capacities of modern radar detection technology has just emerged: lightning fusion technology. The two datasets are intelligently merged and analyzed via the use of sophisticated data processing methods. This article delves into a lightning vision fusion–based intelligent monitoring method for transmission lines and suggests a system that uses algorithms based on deep learning (DL) to automatically record and analyze changes in the surrounding environment of transmission lines, greatly enhancing the accuracy and timeliness of such monitoring. In addition to reducing the need for human involvement and operating expenses, the experimental findings demonstrate that this system successfully prevents missed and false alerts, offering a stronger technical assurance for the reliable and secure functioning of the power system (EPS) [13].

In order to improve the stability and safety of power transmission towers, this study suggested a YOLOv11-based hidden danger identification and detection system. The goal of this system is to introduce an intelligent identification while identification system. Among the several object detection algorithms in the YOLO family, the most recent and cutting-edge one, YOLOv11, stands out for its exceptional detection effectiveness and precision. Here, YOLOv11 has been fine-tuned to spot four things that might pose a threat to electricity poles: bird nests, balloons, trash, and kites. The system's accuracy is 93.8% and its recall rate is 73.3%, which is good. Using PyQt5, we painstakingly constructed an intuitive user interface (UI) to confirm the model's real usefulness. With its integrated image and video detection capabilities as well as its real-time camera tracking and recognition capabilities, the system is able to accurately detect the aforementioned four kinds of hidden dangers and to record all detection results comprehensively, making it very convenient to analyze and process the data afterwards. With its intuitive UI and top-notch performance in real-time monitoring and identification, this system guarantees pinpoint accuracy while being a breeze to use. These qualities have provided a firm foundation for the relevant work that has come after [14]. A technique for power transmission lines of the outside anti-breaking, and more especially a technique for transmission lines in the video anti-abduction, is the subject of the current invention. The following are the stages of the video transmission line technique that are based on the technology of anti-abduction behavior analysis: First, we acquire the picture. Then, we have the motion detector. Then, we have the detection block. Then, we follow the target. Then, we identify the target. Then, we analyze the target's behavior. Finally, we have the foreign anti-breaking alert. In order to meet the demands of an outer anti-breaking power transmission line system, we have developed an intelligent analysis method based on this system's behavior. This technique can accurately identify the type of target behavior and detect, identify, and track moving targets When insulators in electrical systems are covered in snow or ice, it may cause a catastrophic failure in the transmission of electricity in northern nations. Massive economic damage might result from power failure and outages caused by snow or ice. Long wind swoops may also lead to electrical shorts. In this research, we provide a new method of video monitoring a far outdoor 420 kV power transmission line with the purpose of identifying electric insulator snow cover and insulator swing angles. It is the initial insulating snow monitoring system that we are aware of that relies on automated picture analysis methods. We suggest a hybrid approach that combines histograms, boundaries, and template cross-correlations to analyze a variety of situations induced by changes in lighting and weather. Experiments with movies recorded over many months have shown useful and encouraging estimate results. With an average identification rate of 67.6% for low-quality photos and 93% for high-quality ones, our system has produced 9% and 18.1% false alarms for image pixels pertaining to snow on insulators, respectively [15]. When snow or ice builds up on electrical insulators, it may disrupt electricity supply in northern regions via power lines. Massive economic damage might result from power failure and outages caused by snow or ice. Using photographs taken from an outside 420 kV power transmission line, this research suggests a new intelligent surveillance as well as image analysis system that can identify and estimate the amount of snow and ice covering electric insulators in real-time. Also, since wind-induced short circuits occur at very high swing angles, the insulators' swing angles are evaluated. To deal with a wide variety of situations brought on by changes in lighting and weather, hybrid methods that combine histogram, edges, boundaries, and cross-correlations are utilized. Over the course of many months, experiments were carried out on the recorded photos. The suggested methodology has produced useful estimate results, according to the findings. The present method has produced an average detection rate of 67.6% for photos with a high concentration of low-quality pixels pertaining to insulator snows, and a false alarm rate ranging from 9.1% to 18.1%. Using video-based analysis with better camera settings might lead to even greater improvements [16].

Machine learning algorithms like convolutional neural networks (CNNs) excel at tasks like object detection, picture captioning, and voice recognition. When it comes to identifying manufacturing flaws or other details in photos that other machine learning systems may miss, CNNs really shine. Convolutional neural networks (CNNs) may detect patterns that point to faults by investigating massive picture datasets. In manufacturing, power cables play a crucial role in communicating with and operating machinery. More and more focus has been placed on smartening up the power production, transmission, distribution, and storage processes. However, sophisticated ways of detecting the dependability of electrical connections should be a part of the smart grid transition. The distribution and transmission of electrical energy makes use of a variety of electrical wires. Interconnected polyethylene (XLPE) cables are extensively used in power systems as a result of their exceptional mechanical and electrical characteristics. Insulation flaws are a result of shoddy fabrication and installation processes for cable junctions. Interdigital capacitive (IDC) technology has been proposed by some as a means of online XLPE cable monitoring. For power line insulation, some have proposed using continuous wave (CW) terahertz (THz) imaging technology to reveal and locate internal flaws. To predict the physical safety condition of particular power cables, the authors of this study used models that rely heavily on locally obtained bespoke datasets. The goal of the model is to identify faulty electrical cables and replace manual inspection using computer vision and image processing methods. A Convolutional neural network, the Tensorflow library, and the Python programming language are used to create the project. In order to classify power line defects, this study employs a technique based on Convolutional Neural Networks (CNNs). In its latter stages, the study suggests using the same or more datasets and offers methods to identify power line faults in real-time video [17]. The use of AI methods for transmission line quality inspection is detailed in this article. When it comes to efficiently and dependably transferring electrical power across great distances, transmission lines are crucial. Nevertheless, power outages along with security concerns may result from faults and flaws caused by a variety of operational and environmental conditions. The suggested method automatically identifies and categorizes possible transmission line problems and defects using cutting-edge Edge Deployable AI technologies, such as computer vision with Deep Learning. To train our state-of-the-art, highly accurate model, we use an i9 core CPU, an Nvidia RTX 3060 GPU, 6 GB of virtual RAM, and 16 GB of RAM. Our architecture and frameworks are based on SSD and PyTorch. We use TensoRT Engine to fine-tune the learned model before deploying it on the Nvidia Jetson Nano B01. The training and testing of the AI models are done using a comprehensive dataset that includes both still photos and videos of transmission lines. These models have been taught to identify abnormalities and patterns that may be caused by a variety of problems, including corrosion, insulator wear, and damaged conductors. Drones and other surveillance equipment are used to take pictures and videos of the transmission cables as part of the inspection procedure. In order to find problems, the collected data is then examined with the help of pre-trained AI models. With artificial intelligence algorithms, human error may be greatly reduced and errors can be detected and classified with high accuracy and recall, doing away with the requirement for manual inspection altogether. Using a feedback loop utilizing an active learning method, the AI models may be continually updated and enhanced to boost inspection accuracy [18]. Power inspection image diagnostic technique using computer vision is introduced in this study. Use of VisualStudio 2010 in the construction of functional modules includes image import, access to databases, text output, and others. The database may be accessed and modified using ADO technology. We provide a framework and approach for fusing diagnostic results that are based on fusion of many dimensions. Using a genetic algorithm, we set the system's fault diagnostic criteria. Quick and accurate fault diagnosis is realized by retaining vital information and obtaining the lowest expression of knowledge under the assumption of assuring the ideal solution. The technology is effective, quick, and well-suited to large-scale power grids, particularly transmission lines, according to the trial findings. The requirements for inspecting electricity lines may be satisfied. Automated examination of transmission line images is now possible, leading to process standardization and significant efficiency gains [19].

3 Methodology

In order to make transmission systems for electricity more efficient, dependable, and safe, automated power line inspection uses computer vision and deep learning. A common procedure for inspecting electrical lines using computer vision is shown in Fig. 1. The process begins with the use of aerial or ground vehicles, and sometimes more than one imaging tool, to take pictures of the components of power lines. Next, the object identification or segment technique is applied to the pictures. Next, the segmented insulators are assessed by the image classification algorithm, which determines whether they are good or defective. This process culminates in the output of fault detection. From data collection to defect diagnosis, this section outlines the main phases of the process. It should be pointed out that in several instances in the published work, the part of identification step has been omitted and a deep learning algorithm has been trained just for defect detection.

3.1 Data collection

Autonomous power line inspection relies on aerial or ground-based high-resolution photography. The visual information derived from the acquired pictures is invaluable and serves as the foundation for further investigation.

3.1.1 Power line inspection robots

An exciting new development in the automation of power line maintenance and inspection tasks is the rise of power line inspection robots. Climbing robots, unmanned aerial vehicle (UAV) robots, and hybrid climbing-flying robotics are the main categories into which these machines fall. While climbing robots can get high-quality inspection data while rolling along power lines, they have a hard time avoiding obstacles and getting onto the wires. While flying robots make avoiding obstacles simpler and inspections go more quickly, they may not be able to check as thoroughly as humans. In order to conduct more thorough inspections, hybrid robots try to combine the best features of climbing and flying robotics.

3.1.2 Satellite imaging

The possibility of using satellite imaging equipment to keep tabs on transmission lines on a grand scale is being investigated more and more. Even if the level of detail isn't up to par with UAV or helicopter data, satellite photography is nevertheless useful for gauging transmission network health across large regions and seeing patterns in the big picture. Figure 1 Shows Transmission Line Fault Detection using Image Analysis

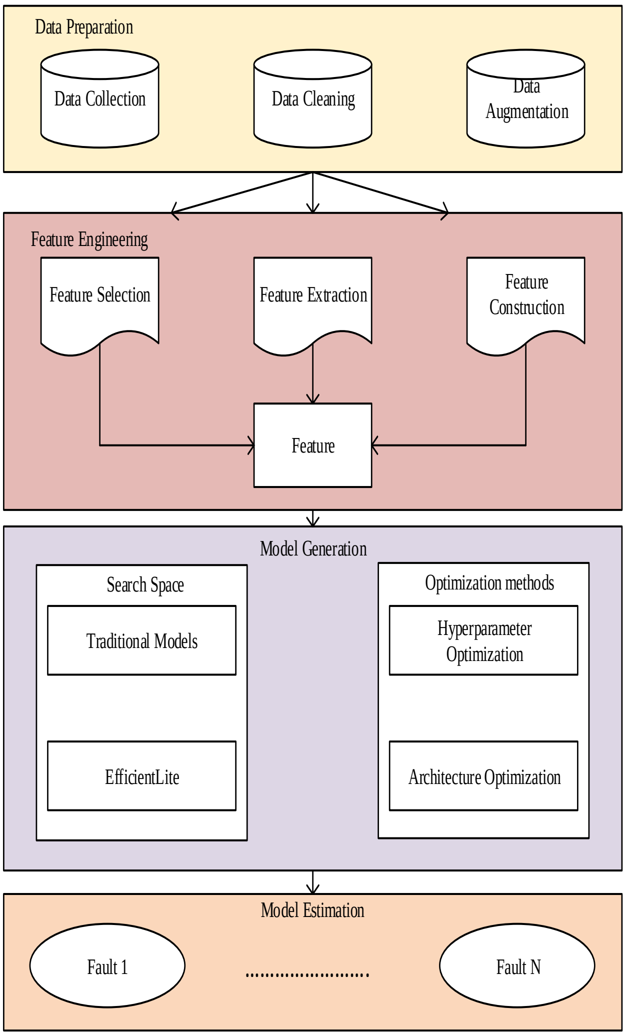

Figure 1: Transmission line fault detection using image analysis

3.1.3 Fixed camera

Power cables are constantly being monitored by fixed cameras placed at critical areas. These cameras are set to take pictures at certain intervals or in response to events. Compared to airborne approaches, they may not cover as much ground and aren't as flexible, but they're still a cheap way to do regular inspections and monitoring.

3.1.4 Unmanned aerial vehicles

Drones, or Unmanned Aerial Vehicles (UAVs), have recently become the go-to tool for power line inspectors looking to capture aerial footage. UAVs with high-resolution cameras can film transmission cables and their parts from different vantage points and distances. Distribution maintenance for lines presents unique problems, but they provide a unique mix of accessibility, flexibility, and safety. Because of its adaptability, extensive visual data may be collected, which improves the accuracy of fault and anomaly detection in power lines. Table 1 below publicly available power line image datasets.

Table 1: Summary of some publicly available power line image datasets

Name	**Component**	**No. of images**
Transmission Towers and Power Lines (TTPLA)	Insulator, Tower, Conductor	1234
Power transmission line dataset	Conductor	1044
Powerline dataset (Infrared-IR and Visible Light-VL)	Conductor, No conductor	8000
(Recognizance - 2) Power lines detection	Conductor	16 078
Chinese Power Line Insulator Dataset (CPLID)	Insulator	848

3.2 Colour conversion

Preprocessing is frequently necessary to make the raw pictures acquired during data gathering more suitable for analysis. To prepare the picture for processing, it may be necessary to do tasks such as enhancing the image, reducing noise, and correcting geometric deformities and lighting conditions. These improvements guarantee the efficacy of the following computer vision techniques.

Correct the supplied image's colors using the LAB channels. In order to make the input image's pixel values conform to the reference image's color statistics, the following formula is applied to each channel (L, A, B):

$$y = \left(p - \mu_{i}\right) \cdot \left(\frac{\sigma_{j}}{\sigma_{i}}\right) + \mu_{j}, \quad (1)$$

where:

- i and j are the identifiers of the input and reference image,
- p is the original pixel value in the input image,
- μ_i is the mean of the input channel,
- μ_j and σ_j are mean and standard deviation of the reference channel,

- y is the corrected pixel value,

If the reference and input pictures have different color statistics, the pixel values of the input image will be changed accordingly. Restore the initial color space to the rectified picture. We provide many data-level approaches to learn with small training sets. Our main areas of interest are data augmentation, synthetic image production, and color correction for synthetic image repair. Being training-time procedures, it is crucial to highlight that these data-level methodologies achieve the objective of lightweight models and quick on-board computing.

Video image capturing technology can operate in complicated backdrops thanks to the sensor on the tower, and transmission cables have long been subjected to dynamic outside situations. Nevertheless, the pictures often become hazy because of certain things. Various sorts of elements, both internal and external to the system, may have a significant influence on the quality of the video pictures collected and, by extension, on the efficacy and precision of recognition. That is why it is crucial to have efficient means of reducing background noise. In most cases, the filtered pixels comprise neighbouring pixels, and a typical filter is a structure template with four or eight neighbouring filters.

3.3 Data augmentation

In order to make the dataset more diverse and the model more capable, our research used a number of data augmentation strategies. They comprised:

- Rotation at 90, 180, while 270 degrees to strengthen the model against changes in object orientation while perspective
- Flipping vertically. It really shines when working with multi-perspective symmetrical items or settings.
- Varying the contrast and brightness at random. The model's robustness to changes in illumination and pixel intensities may be enhanced by arbitrarily altering the contrast and brightness of training photos. To make sure the model works in real-world scenarios, it would be great if the photographs could be taken in a variety of lighting settings.
- Introduce additive Gaussian noise into the training set. In order to simulate defects and environmental variables that impact the acquisition in real life, this noise generates small oscillations in the picture data. Because of how common the Gaussian distribution is in the real world; it has gained widespread acceptance here.

Following a normal distribution, the probability density function changes to:

$$N(\chi : \mu , \sigma) = \frac{1}{\sqrt{2 \pi \sigma^2}} \exp \left(-\frac{1}{2}(x - \mu)^2 / \sigma^2\right)$$

(2)

A random variable x is taken from this distribution and inserted into the polluted pixel, where μ stands for the mean of the Gaussian distribution and σ for the standard deviation. This work used additive Gaussian noise (N (1,3)) to simulate real-world noise changes, where the mean is 1 and the standard deviation is 3.

3.4 Fault diagnosis

The last step of automatic power line inspection is fault diagnosis, which is done by feeding images or identified elements into models using deep learning. These models then attempt to identify any problems. Operators may prioritize repair and maintenance tasks by using deep learning models to assess the severity and breadth of defects. With the help of these models, we can better understand the power transmission mechanism as a whole and take measures to avoid accidents and outages. A strong and fast method for discovering and diagnosing a range of defects has emerged: visual inspection combined with state-of-the-art computer vision algorithms. The capacity of computer vision to precisely evaluate power line components is revolutionizing electrical grid dependability and maintenance by identifying and fixing insulator faults, conductor difficulties, tower abnormalities, and grounding difficulties. This section explores how computer vision and deep learning may be used to diagnose issues in power lines and related equipment. It highlights how this technology has the potential to improve the uptime and efficiency of vital power transmission infrastructure. Parts of transfer and distribution systems that deal with power lines include pin bolts, dampers, and suspension clamps. These parts take up a little amount of visual real estate in the pictures—just a few pixels—and are very small in comparison to the transmission line tower as a whole. Consequently, robust algorithms that use deep learning and intense processing of images are needed for precise defect detection in these elements. A new set of difficulties arises when trying to detect fittings for power lines, such as pin bolts, dampers, and suspensions clamps. Because of their diminutive size in comparison to the electrical transmission system as a whole, detecting, and classifying these connections is an exceptionally challenging undertaking.

3.4.1 EfficientNetLite architecture

The outstanding performance of EfficientNetLite in a number of tasks has contributed to its rising popularity. Introduced as a more lightweight version of EfficientNet, it prioritizes low-memory and low-energy usage in resource-constrained situations, including edge devices. To maximize the model's performance without drastically increasing its computing cost, this design makes use of compound scaling, which equalizes depth, breadth, and resolution. For practical uses with constrained computing resources, its adaptability and remarkable performance-to-efficiency ratio make it an attractive option. The study's primary application of EfficientNet-B0 is seen in Fig. 7. The construction components allow for a complete description of the architecture's 237 levels; for specifics, see the supplemental materials.

A customized loss function called Focal Loss was developed to tackle the problem of class imbalance in classification tasks. A typical crossentropy loss might cause the model to zero down on the majority classes while ignoring the minority ones in cases when some classes have much less samples than others. By reducing the weight of instances that are simple to categorize and increasing it for examples that are challenging to identify, Focal Loss alters the cross-entropy loss. To accomplish this, a modulating factor is introduced during training to enhance the effect of misclassified samples:

$$\mathrm{FocalLoss} = -\sum_{i=1}^{N} (1 - p_i)^{\gamma} \log(p_i) \qquad (3)$$

where:

- $p_i \in [0,1]$ is the model's predicted probability of the i-th class,
- γ is the modulating factor with tunable focusing parameter $\gamma \geq 0$,
- N is the total number of classes.

One may gradually change the pace at which simple samples are down-weighted by adjusting the parameter γ. Focal Loss is equal to the cross-entropy loss when γ is zero. The effect of misclassified instances (Lin) is amplified as the modulating factor's influence is stronger when γ is raised. Figure 2 showsEfficientLite Architecture.

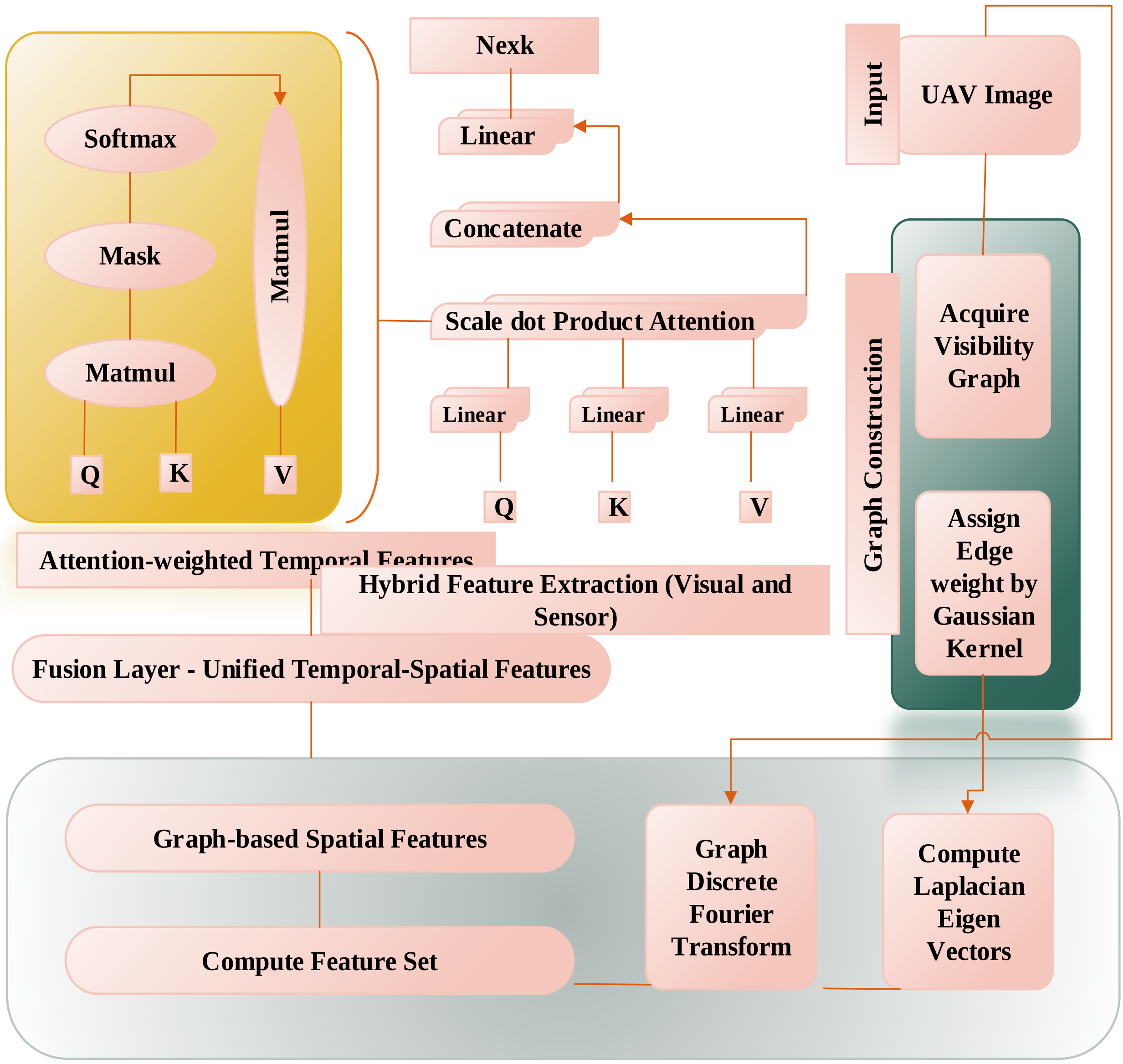

Figure 2: EfficientLite architecture

3.4.2 Feature subset fromimages andsensors

One of the most important steps in image analysis is extraction, which may be done using a variety of extracted features. Some examples of these methods include colour the process of segmentation watershed methods, region growth, edge detection, boundaries classification, threshold segmentation, and segmenting an image. You may use these image feature points to help determine find the source of the network that transmits mountain fire. Each pixel's brightness is dramatically increased relative to its neighbours due to a mountain fire. To find the pixel spots, you could tweak the temperature parameters and select a flashpoint threshold. We capture the image using surveillance equipment, and then process it with image recognition technologies to reduce noise. If the calculated temperature value at the linked highlight is greater than this threshold, then the point is considered the ignition point.

Once the decision is made on which independent connectivity zones to segment, specific interference locations may be restored as separate regions. Here, comparing the different regions makes it possible to exclude regions that don't add anything to the segmentation result. A visually consistent feature that doesn't change with the light is a texture element. Neighbouring the image pixels is the gray space distribution, which includes energy, entropy, and inverse moments. A measure of energy, the Gray level co-occurrence matrix is equal to the squares of all of its individual elements. It measures the image's texture thickness plus the degree of Gray level homogeneity. A measure of the information richness of a picture, the entropy, describes the complex and non-uniform textures of the flame image. The homogeneity of the image texture is shown by the inverse moment, which measures local variations in the picture texture. As the distance increases, there is less fluctuation among texture regions and more constant variation at the local level. By comparing the components in the observed spatial grayscale in both column and row directions, it becomes simpler to find the colour extension of the flame image development.

The most reliable method for detecting network safety issues is manual inspection; nevertheless, this approach is labour-intensive, prone to human mistake, and limited by factors such as inspections cycles, environmental factors, and inspectors' skill levels. Not only are there many limitations and risks, but real-time detection and warning of transmission line anomalies is also challenging. Table 2 shows Feature subset.

Table 2: Feature subset

Feature Subset	**Feature Description**
Feature subset I	the transmission line's reactive and active power
Feature subset II	The phase angle and magnitude of the bus voltage, the active and reactive powers of the transmission line
Feature subset III	voltage and current across transmission lines, voltage and current through generators, and voltage and current through loads
Feature subset IV	the magnitude of the bus voltage, the phase angle, the reactive as well as active power of the generators, the active and reactive power of the loads, and the active and reactive power of the transmission lines

With the exception of the positive samples at hand, the remaining 2(N-1) sample pairs are negative samples; hence, the overall number of samples after expansion is 2 N. Here, N is the number of samples in a batch. Cosine similarity is a measure of the distance between samples; where u and v are the feature space representation vectors of two samples, respectively, we can write the distance between pairs of samples as:

$$sim(u,v) = \frac{u^T v}{\|u\|\|v\|} \quad (4)$$

In self-supervised learning, info noise contrastive estimation (NCE) is employed to compare loss functions and maximize the probabilistic optimization theory of correct sample pairs via log-likelihood estimates. This approach helps to avoid the computational complexity that comes with an excessive amount of negative sample pairs. that is, the distance between positive and negative sample pairs is the denominator and the distance between positive and negative sample pairs is the numerator. $\boldsymbol{z}_i$ is the feature representation of the sample, $\boldsymbol{z}_{j(i)}$ standing for the positive representation of the sample features after data augmentation, z_a for the negative representation of the sample features, and τ for the temperature coefficient.

To better enable future model training, instance transfer aims to increase the size of the destination domain's sample pool. The minimal distance approach is used to identify the source domain samples that are most comparable to the destination domain and may be transferred. Here, x^5 represents the samples from the source domain, x^T represents the samples from the target domain, and the chosen samples may be represented as:

$$\begin{cases} dist(x^S, x^T) = sed(x^S, x^T) \\ \widehat{x}^s = \{x^s \mid dist(x^s, x^T) < \theta\} \end{cases}$$
(5)

where $\hat{x}^S$ is the distance threshold, and represents the chosen samples. In order to begin updating the model, the chosen samples will be used.

3.4.3Loss Function

Sparse categorical crossentropy and Focal Loss are two examples of the many loss functions used to improve model performance. For multiclass classification problems, the former loss function is often utilized since it quantifies how different the anticipated probability distribution is from the actual target label. This loss can be described for a training set of N instances as:

$\mathrm{J}(\mathbf{w}) = -\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} [\mathrm{y_i}\log(\hat{\mathrm{y}}_\mathrm{i}) + (1-\mathrm{y_i})\log(1-\hat{\mathrm{y}}_\mathrm{i})]$,

where:

- w refers to the model parameters, and
- $\mathrm{y_i}$ and $\widehat{y_i}$ are the true and predicted labels.

4 Experimental validation

4.1 Experimental setup

The studies were conducted on a computer that has a 32 GB RAM, an NVIDIA GP107M GeForce GTX 1050 Ti Mobile GPU, 12 processors, and an Intel Core i7-8750H CPU operating at 2.20 GHz (Ubuntu 22.04.3). Python (version 3.9.16) and TensorFlow 2.7.0 were the tools used to build the project.

Our experimental investigation has several goals. Our goal is to examine how the potential deep model capabilities of OPS-SAT may be affected by data augmentation with synthetic data creation. In Table 3 showed by Local weather sensor specification sheet. In order to get good performance in FSIC, we additionally adjust the hyperparameters of individual models, which is something we cover in depth.

Table 3: Local weather sensor specification sheet

Feature	Range
Temperature [°C]	0~60
Relatively Humidity [%]	0~100
Average Wind Speed [m/s]	0~60
Wind Direction [Degree]	0~360
Rainfall [mm/h]	0~200
Pressure [hPa]	600~1100

We devised five experiments based on different variants of the dataset to tackle these aims:

- The primary data set.
- A dataset that has been enhanced from the original.
- A picture database supplemented with digitally created images.
- A variant of the dataset that has been artificially constructed, with its colors adjusted.
- All three of the above as a set.

We explored two loss functions and conducted a thorough process of hyper-parameter tweaking across all of these different setups. Varying studies used varying numbers of cross-validation folds to make sure the findings held up against diverse data distributions. Notably, by including transfer learning along with pre-training on two more datasets, variation and underwent an additional level of complexity. Notably, the transfer learning approach was not used in the first four tests; all that was done was pre-training using ImageNet. In the last (fifth) study in this series, transfer learning was implemented.

Over the course of these five main configurations, 107 trial runs were carried out, with a total duration on a local system reaching 38 hours. There was a constant use of a single test set that included 40 unique photographs, with 5 images per class. The model was kept in the dark about these test pictures for the duration of the studies to make sure they were new to it. At last, we ran the model through its paces on this test set, evaluating it using measures like multi-class accuracy and Cohen's Kappa values. All models were originally K-fold cross-validated; thus the metrics include both the average and standard deviation of the validation accuracy for the K models that were trained. A thorough review is conducted on the test set for the model that achieved the greatest validation accuracy.

4.2 Experimental results

Here we show the results of five primary studies that used the five different datasets mentioned above. Important hyperparameters investigated in depth during the various experimental runs include the batch size, the loss function, the early stopping patience variable (the number of epochs without enhancements in the loss value), and the values of the Focal Loss hyperparameters (α and β). To optimize memory use and meet the computational needs of processing many samples each iteration, the batch size was intentionally lowered while dealing with the dataset variant that is defined by a greater sample size. The batch size was more freely changed to maximize training dynamics while resource consumption in cases involving a dataset fluctuation with a smaller sample number.

According to the regulations of the competition, EfficientNet-Lite0 was chosen as the model. This amount of alpha does not favor one class over another, and we used Focal Loss with α=0.5 and γ=2. But this gamma number shows that you really want to focus in on instances that defy easy categorization. Since starting training without any predetermined weights produced unsatisfactory results, the model was pre-trained using ImageNet weights instead of transfer learning. To prevent overfitting, the early halting method was used with a patience value of 3. During training, 2-fold cross-validation was used; the best model was derived from one of the two training sessions; half of the training information was used as validation data. The model was further adjusted to reduce the likelihood of overfitting by setting a dropout hyperparameter of 0.5. Finally, an 8-batch training session was used to train the model with the Adam optimizer. Refer to the supplemental materials to confirm the GPU memory allocation while the number of threads utilized by the CPU during training. Importantly, we used the test dataset that was provided around thirteen months after the competition finished to get our findings.

We used four important metrics—accuracy, precision, recall, and F1 score—to evaluate our models' performance. All four of these measures—true positive, false positive, true negative, along with false negative—contribute to a holistic picture of the model's performance. The accuracy may be described as the percentage of forecasts that are accurate, including both positive and negative predictions.

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

in where TP stands for true positives, TN for true negatives, FP for false positives, with FN for false negatives.

A measure of accuracy in predicting future positive observations relative to all positive observations anticipated is called precision, which is sometimes called positive predictive value.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The percentage of true positives that were accurately anticipated is called recall, which is also called sensitivity.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Finally, to measure the equilibrium between the two, we have the F1 score, which is the harmonic mean of the accuracy and recall weights. Whenever there is a discrepancy in the distribution of data classes, it becomes quite helpful.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

To provide a thorough assessment of the model's efficiency across time, the aforementioned metrics were calculated at the conclusion of every epoch. An analysis of the relative merits of feature transfer learning algorithms trained from scratch and those trained using real-world data. For each experimental setup, the best outcomes are shown by bold writing is given in Table 4.

Table 4: Comparison analysis

	Model	Test Loss	Test Accuracy	Precision	Recall	F1	G-Mean
ResNet18	Scratch Model	0.292	87.6%	92.1%	94.6%	0.945	0.888
	Transfer Learning	**0.176**	**96.1%**	**94.2%**	**99.5%**	**0.965**	**0.955**
ResNet50	Scratch Model	0.377	84.0%	**89.4%**	84.8%	0.878	**0.867**
	Transfer Learning	**0.285**	**88.4%**	86.7%	**97.7%**	**0.943**	0.889
DenseNet161	Scratch Model	0.312	96.2%	89.6%	98.7%	0.922	0.896
	Transfer Learning	**0.168**	**95.6%**	**95.7%**	**99.7%**	**0.964**	**0.923**
ShuffleNet v2	Scratch Model	0.466	78.2%	76.8%	88.2%	0.812	0.790
	Transfer Learning	**0.311**	**93.8%**	**94.0%**	**97.4%**	**0.989**	**0.920**
MobileNet v2	Scratch Model	0.423	88.0%	**82.2%**	79.5%	0.840	0.878
	Transfer Learning	**0.267**	**93.9%**	88.8%	**99.7%**	**0.924**	**0.845**
EfficientLite	Scratch Model	0.488	86.1%	89.6%	84.0%	0.889	0.812
	Transfer Learning	**0.170**	**94.6%**	**95.9%**	**98.4%**	**0.946**	**0.975**
Wide ResNet50-2	Scratch Model	**0.280-**	87.5%	**90.6%**	94.9%	0.918	**0.895**
	Transfer Learning	0.319	**86.9%**	87.1%	**96.6%**	**0.940**	0.812

5 Conclusion

The lives of humans are intricately bound up with transmission lines. Locate a high-voltage wire for transmission by means of a network camera attached to the line and delivering live video to a server running an algorithm for digital image processing. We place a premium on transmission line safety. As a result, we draw from a wide range of domestic and international approaches for analysis in our research. The State Grid often employs the analysis-based approach of using unmanned aerial vehicles (UAVs) for monitoring, which relies on aerial photography but is time-sensitive and requires substantial funding. Given the present state of technology, we believe that deep learning techniques for monitoring would be an improved alternative to human laborers due to their lower cost and ability to replace them. However, studies using deep learning techniques are few.

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