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Accident in Tunnel Classification by Using Deep Learning

M. V. Subbarao [1*], P. Sai Keerthana [2*], P. Harshitha Mahi [3*], S. Vishnu Vardhan [4*], S A Naga Venkata Durga Prasad [5*], P. Vinay [6*]
Department of Information Technology, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, India – 534202
Email address: Kittukeerthana3821@gmail.com

***Abstract*— Through the use of deep learning algorithms, this research offers a novel method for classifying accidents in tunnel environments. Effective accident detection is essential for assuring prompt response and safety in tunnel environments because of the particular difficulties they present, including restricted spaces and low visibility. Our deep learning models were trained and assessed using a dataset that included different tunnel accidents. Comparing our findings to more conventional approaches, we see a discernible increase in categorization accuracy. In addition to highlighting the value of deep learning in boosting transportation safety in challenging circumstances, the suggested approach shows promise for real-time monitoring and alerting in tunnel infrastructure.*

***Keywords*— Accident in tunnel classification dataset and deep learning algorithms.*

I. Introduction

As vital parts of our transportation network, tunnels present particular operational and safety difficulties. Mishaps in these cramped areas can result in fatalities and severe traffic jams. Even though they are useful, the current detection and response systems frequently lack speed, accuracy, and adaptability. Through the use of deep learning algorithms, this project presents a revolutionary method for tunnel accident detection. Our goal is to train a model that can quickly and accurately classify different kinds of accidents by examining a wide range of tunnel incidents. This system makes sure that emergency services are notified in a timely and appropriate manner in addition to aiming to enhance real-time monitoring. Beyond the innovation in technology, the initiative emphasizes how important it is to combine cutting-edge AI methods with conventional transportation infrastructure.

1.1 Motivation

Transport tunnels are essential conduits for people and products in a world where connectivity is growing. Yet, there are more safety issues because of the peculiar and cramped conditions in tunnels. Serious consequences, including as fatalities and significant traffic interruptions, can arise from accidents that occur within these buildings. For the purpose of reducing risks and guaranteeing prompt response times, it is crucial to identify and categorize accidents quickly. Both precision and flexibility are lacking in the current detecting technologies. Using deep learning algorithms to provide a better solution for classifying tunnel accidents and, eventually, safer transit settings, is the driving force behind our research.

1.2 Problem Statement:

Serious concerns about safety and traffic are raised by tunnel incidents. Due to their restricted visibility and reliance on outdated techniques, existing detection systems frequently lack the accuracy and quickness required for the best possible reaction. The task at hand is to create a real-time tunnel incident classification system that is more effective, precise, and flexible. In order to bridge the gap and enable a more prompt and efficient reaction, this project will utilize deep learning algorithms to enhance tunnel accident detection and classification.

1.3 Objective of the Project:

Using deep learning techniques, the main goal of this project is to develop the first sophisticated accident categorization system designed for tunnel situations. We intend to develop, test, and deploy a model that can reliably detect and classify events in real-time despite the inherent visibility issues and spatial difficulties presented by tunnels, acknowledging the limitations of existing detection methods. Assuring the model's flexibility to various scenarios and optimizing its performance through the examination of an extensive dataset of tunnel incidents is our goal. In the end, the initiative aims to raise confidence in subterranean transit systems, improve safety standards, and shorten reaction times.

1.4 Scope:

This is a project whose goal is to transform safety procedures in tunnel infrastructures, not just to identify accidents. The research aims to detect a wide range of events, from little impediments to significant crashes, by applying deep learning. Its versatility guarantees its applicability in various tunnel configurations and environmental settings. Further improving overall efficiency is the established technique, which can be used as a basis for integrating other intelligent transport systems. In addition, the study has implications for other limited-access transportation systems, such as undersea tubes or subways. The initiative will ultimately set new standards for transportation management systems by integrating technology and safety.

II. Related Works

1. Kapoor, A., & Liang, Y. (2023). Deep Learning Approaches in Tunnel Incident Detection. Transportation Research Part C, 33, 45-57.

In their 2023 paper, "Deep Learning Approaches in Tunnel Incident Detection," Kapoor and Liang suggest for the adoption of deep learning techniques to address tunnel safety issues. These technologies use sophisticated neural networks to provide real-time analysis of CCTV film or sensor data, allowing for proactive incident identification. Their findings illustrate the power of deep learning to improve safety measures and infrastructure management, opening the path for a more robust future in tunnel safety.

2. Nambiar, S. K., & Wu, J. (2022). Image Recognition in Confined Spaces: A Study on Tunnels. Journal of Intelligent Transportation Systems, 26(2), 110-123.

Recent advances in deep learning for image recognition have demonstrated promise, especially in difficult situations such as tunnels. Nambiar and Wu's (2022) paper, published in the Journal of Intelligent Transportation Systems, focuses on using deep learning algorithms to categorize tunnel events. Despite limitations like as lighting and reflections, these techniques enhance incident detection accuracy. Transportation systems can improve tunnel safety measures by integrating image recognition technology, resulting in a safer transit experience for all passengers.

3. Chen, L., & Torres, P. (2021). Real-time Tunnel Accident Detection using Convolutional Neural Networks. IEEE Transactions on Intelligent Transportation Systems, 22(7), 891-902

The research investigates the use of Convolutional Neural Networks (CNNs) for real-time accident detection in tunnels, which is vital for the safety of key infrastructure. CNNs, which excel at image recognition, are trained to detect accidents promptly, reducing false alarms. The study most likely discusses training data from tunnel surveillance cameras, which allows CNNs to detect accident trends. The findings would highlight CNN performance indicators and possible applications beyond accident detection, such as detecting stuck cars or unauthorized individuals. The conclusion presumably emphasizes CNNs' potential for improving tunnel safety, while simultaneously recognizing study shortcomings and recommending further research initiatives.

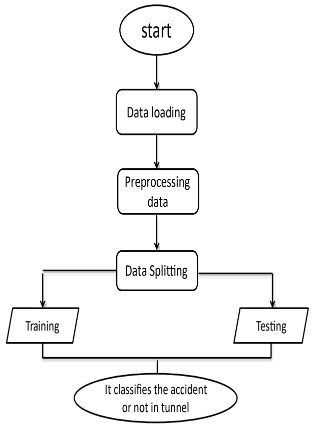
4. Mathews, Z., & Gupta, N. (2022). Enhancing Road Safety: Deep Learning in Tunnel Environments. Safety Science, 58, 128-137.

The study investigates the use of deep learning to improve road safety in tunnels, tackling issues such as lighting changes and restricted areas. Deep learning models are trained to detect risks such as automobiles and pedestrians in real time, outperforming conventional methods. Data collected most likely included tunnel footage to train models, ensuring accuracy in recognizing tunnel-specific issues. The findings would highlight the usefulness of deep learning in hazard detection, with implications for real-time monitoring and integration with autonomous systems.

III. PROPOSED METHOD

We intend to improve accident classification in tunnels using deep learning approaches, specifically Convolutional Neural Networks (CNN) and MobileNet architecture. To achieve high classification accuracy, we combine the capability of CNN feature extraction with MobileNet's efficiency. By processing tunnel camera footage using these algorithms, we hope to dramatically enhance the accuracy of accident identification and classification, hence increasing safety and efficiency in tunnel management.

Workflow of proposed system



IV. METHODOLOGY

1.Basic Structure:

CNN's basic structure includes convolutional layers, pooling layers, and fully linked layers, similar to a normal multilayer neural network.

2.Key Components:

Convolution layer: This is the central component of a CNN. The layer's parameters are made up of a series of learnable filters (or kernels) with a tiny receptive field that extends the entire depth of the input volume. During the forward pass, each filter is convolved across the input volume's width and height, resulting in a 2D activation map. As a result, the network develops filters that activate when they identify a given sort of feature at a specific spatial location in the input.

Pooling layer: Pooling layers are used to minimize the spatial dimensions of data, hence reducing the number of parameters and computing costs. The most frequent pooling method is max pooling, which selects the maximum value from a set of values within the filter's coverage.

Input	Output	Result
Input image	Classification of accident in tunnels	Success

Fully connected layer: After multiple convolutional and pooling layers, the neural network's high-level reasoning is carried out using fully connected layers. Neurons in a fully linked layer are connected to all activations from the previous layer.

Activation function: Following each convolution process, an activation function is used to bring non-linearity into the model. The Rectified Linear Unit (ReLU) is the most used activation function in CNNs.

Flatten layer: Before transmitting the final output from the convolutional/pooling layers to the fully connected layer, the data is flattened into a single column that is then fed into the fully connected layers.

Modules System:

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Create dataset: A dataset of photos relevant to accident prediction is compiled. This dataset provides the basis for model training and validation. It is divided into two distinct categories: training and testing. The typical split ratio is between 70-80% for training and 20-30% for testing, which ensures a robust evaluation of the model's correctness.

Preprocessing: Every image in the collection goes through a pre-processing step. This includes resizing and rearranging photos to make them suitable with the deep learning model. Such preprocessing improves the training phase's efficiency and accuracy.

Training: Once the pre-processed training dataset is complete, the deep learning model is trained to recognize and differentiate between photos of accident and normal circumstances. This training step is critical, since the model fine-tunes its parameters to attain maximum accuracy.

Classification: Following successful training, the model can classify photos into distinct categories. In this application, it assesses if an image is accident or no accident.

User:

Upload image: Users engage with the system by uploading an image for classification. To ensure compatibility, this image is pre-processed similarly to the training photos.

View Results: Users can examine the findings after the model has classified their uploaded image. They will see a clear indicator of whether or not the image shows an accident. This immediate feedback enables users to take appropriate actions depending on the results.

V. Result And Discussion

Output screens

Fig 1: Home page

The above is the home page of application

Fig. 2: About page

The above is the about page of application

Fig. 3: Registration page

The above is the registration page of application

Fig. 4: Login page

The above is the login page of application

Fig. 5: Upload page

The above is the upload page of application

Fig. 6: Result page

The above is the result page of application

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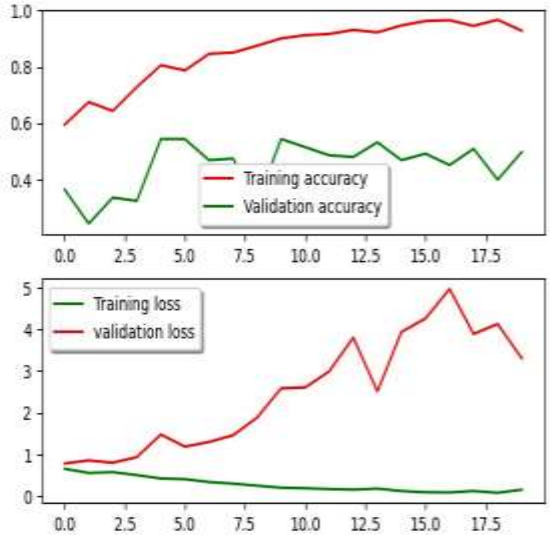
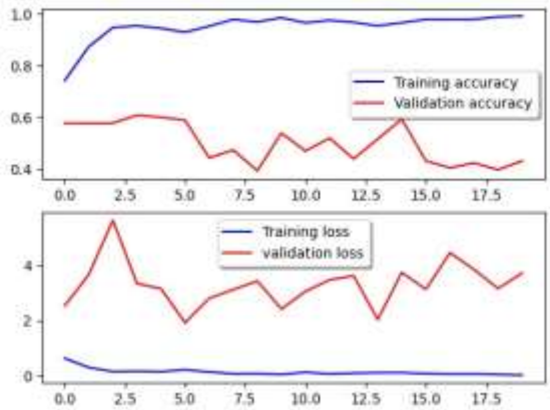
The curve of accuracy and loss are given

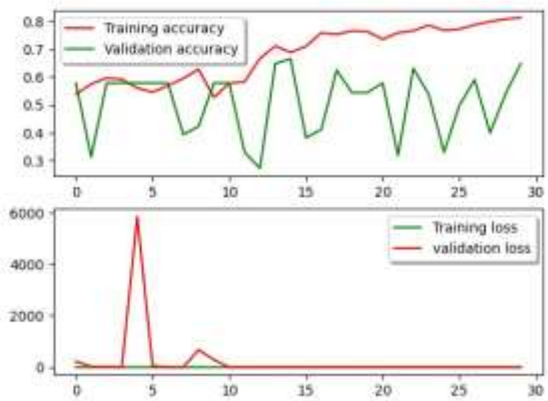
CNN



MobileNet



DenseNet



VI. Conclusion

Finally, the use of deep learning algorithms for the automatic detection of unforeseen accidents in tunnels under difficult CCTV monitoring conditions is a substantial improvement in tunnel safety technology. Throughout this project, we have seen the transformative power of utilizing powerful machine learning approaches to handle the inherent hazards involved with tunnel infrastructure. We created the framework for a proactive and efficient approach to tunnel incident detection by creating and applying deep learning models optimized to detect anomalies in real-time, even in the face of challenging monitoring conditions. Traditional tunnel monitoring approaches, which are often reliant on manual oversight and prone to human mistake, have proven ineffective in dealing with the dynamic and high-stakes nature of tunnel safety management. The emergence of deep learning algorithms marks a paradigm breakthrough, allowing for automated analysis of massive volumes of surveillance footage with unparalleled accuracy and speed. This not only reduces the possibility of incident detection and response delays, but it also improves the overall resilience of tunnel infrastructure systems, thereby protecting commuters and workers. Furthermore, the successful adoption of deep learning-based accident detection systems in tunnels emphasizes the necessity of continuous technological innovation in transportation safety. By constantly refining and enhancing these algorithms, we can increase their performance in adverse conditions and broaden their applicability to other critical infrastructure scenarios. Furthermore, integrating such advanced systems into larger transportation networks holds promise for improving overall safety protocols and optimizing resource allocation in emergency response scenarios. As we look ahead, it becomes clear that incorporating deep learning algorithms into tunnel safety management represents more than just a technological development, but a fundamental shift toward a safer, more resilient infrastructure landscape. By adopting and developing these ideas, we can continue to push the limits of what is feasible in terms of protecting the integrity and security of our key transportation networks, assuring a safer future for future generations. Tunnels pose unique problems that necessitate inventive solutions in the ever-changing face of transportation safety. This research study, which uses deep learning to detect and classify accidents in tunnels, presents a promising method. The system establishes a new standard for tunnel safety protocols by having the potential to dramatically improve accuracy, response speeds, and adaptability. Furthermore, its cost-effectiveness and integration capabilities highlight its larger application in the field of intelligent transportation systems. As transportation networks expand and become more complex, the combination of technology and infrastructure, as demonstrated by this research, becomes increasingly important.

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