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POTHOLE DETECTION FORM IMAGES AND LIVE CAMERA WITH LIVE LOCATION USING DEEP LEARNING

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***Abstract*— Pothole detection is crucial for ensuring road safety and reducing vehicle maintenance costs. This project leverages Convolutional Neural Networks (CNN) for real-time pothole detection using live camera feeds and static images. The CNN model is trained on a diverse dataset of road images, enabling it to accurately identify potholes under various lighting and weather conditions. The system aims to provide an efficient, automated solution for identifying and reporting potholes, enhancing road maintenance efforts. we propose an approach to detect potholes real time by Deep learning which will fulfil the requirements. We have applied CNN based VGG19 Deep learning algorithms on our collected dataset's features and got promising results. And our model will help to detect both from images and live video Potholes can holes on the outermost layer of roads that measure more than 75 millimeters horizontally and 20 millimeters deep. They are caused by overloading cars, poor structure, blocked water during the rainy season, decay of rocks, and occasionally by all of these factors together. According to statistics, 58,208 collisions caused more over 57,000 injuries and over 57,000 fatalities in our nation during the past 20 years. And potholes are a big factor in many of these incidents. Due to this pothole, cyclists are in serious risk today. To identify potholes at any time and warn vehicles to avoid any discomfort or accidents, a reliable detection apparatus is required. Although considerable work has been done on this issue, we provide a method that will meet the demands for real-time crater detection using deep learning. On the attributes of our amassed dataset, we tried a few deep learning algorithms and obtained encouraging results. Additionally, our model's ability to spot potholes in the moment will help save many lives.**

***Index Terms*— Machine Learning, Pothole Detection, TensorFlow, Convolutional Neural Network, Image Classification**

I. INTRODUCTION

Roads serve as the foundation for connecting and transporting individuals across various locations. Road sizes vary depending on how they are used. For instance, roads are wide enough to accommodate several lanes that are intended for heavy traffic. However, streets within towns are built to be narrower and have one or two lanes. Because roads are essential to people's everyday lives, they must undergo routine maintenance to remain safe and functioning. Due to the sheer number of roads in a particular nation, it is impossible to continuously check the condition of the roads; as a result, pothole creation cannot be predicted. Road problems are mostly caused by pavement deterioration. There are three categories of pavement distress: fracturing, pushing, corrugation, and rutting of the pavement disintegration (raveling and peeling), and ageing (fatiguing, spalling, and cracking). This project focuses on potholes, which are regarded as the greatest pavement distress and are unexpected in their production. The principal cause of these distortions can be attributed to a confluence of atmospheric factors and pavement strains from driving. Potholes are a global issue because they cost individuals and governments billions of dollars each year Automobile crashes claim the lives of 1.25 million people each year, and 34% of these incidents are caused by potholes. Three methods may be used to identify potholes the vibration technique, the three-dimensional reconstruction methodology approach (using the Kinect sensor for the method, stereoscopic vision procedure, and laser scanning method), and the vision approach. Table 1 lists and examines several methods for detecting potholes based on the technology employed, response and sensing time, interpreting, cost, pothole characterization, and detection precision . In the past, a team of personnel would check recorded digital videos taken of the roadways to find potholes. This process costs money and takes time. In a border detection technique was employed.

The project is a machine learning project to analyze the roads and detect whether it contains a pothole to help the driver of the vehicle to take the required measures in time to avoid a severe accident. The machine learning model uses Convolutional Neural Network which is a type of neural network. Potholes are the breaks on the roads which can cause due to various reasons such as rain, and expansion and contraction of ground water. These are one of the major causes for road accidents. As autonomous vehicles are entering the market, the need for them to understand the risks on the road becomes important. This project uses machine learning, which is a part of Artificial Intelligence which deals with the automation of tasks by the machine itself. It also has the ability to learn from its past mistakes without being specifically programmed

II. LITERATURE REVIEW

In recent years, researchers have significantly increased their interest in pothole detection because of their potential impact on road transportation. In this context, several efforts have been made to develop viable solutions for detecting potholes in several approaches, e.g., image-based pothole detection for ITS (Intelligent Transport System), real-time pothole sensing by accelerometer for smart-phones, detection of potholes using black box cameras, laser imaging and detecting potholes by using CNN. This section summarizes relevant literature survey papers, clarifies the differences and provides a research gap contribution to a paper. In the following section we examine some existing surveys on those issues. The traditional processing object detectors use available crafted representations to extract low features.

Potholes were detected in previous post-processing studies, and there were several videobased methods that identified potholes and counted their number over consecutive frames. A collection of one-of-a-kind frame combinations was accumulated. They were converted to blurring grays-cale and then morphological and part detection techniques were applied to identify contours that could then be ana-lazed with a Hough transform to extract functions. Ten both on the basis of 2D color images, applied fuzzy-manner clustering set of rules and morphological reconstruction techniques to determine potholes on asphalt pavements. Using image processing, Nienaber et al. Idented potholes on roads and removed unwanted regions such as cars and plants from the image.

For finding potholes, the frames are processed using simple processing techniques, Canny filters, and contour detection. Experimentally, 81.8% precision and 74.44% recall was achieved. Although the accuracy values are pleasing in the testing, itis not guaranteed that the same strategy will result in the same accuracy on every type of road. Machine learning (ML) methods are increasingly used to detect digital images with potholes that can be recognized through trained models. Support vector machines (SVMs) were used to analyze road information and detect potholes.

Potholes were detected using an image feature based on histograms, and pothole detection was determined using a non-linear SVM. The authors trained an SVM to recognize potholes in labeled images using a set of scale-invariant features. For detecting potholes, these methods achieved an accuracy of 91.4%. Hoang et al. considered least-squares SVM along with neural network to detect potholes with an accuracy of 89%. The forensic-based investigation (FBI) metaheuristic was recently incorporated into the SVM by Hoang et al. To optimize the pothole detection accuracy, experiments were conducted on and accuracy of 94.833% was achieved.

Despite significant accuracy achieved by the machine learning approach, they ran into these challenges: (1) manually extracting features must be done by experts to improve the accuracy performance during the pothole detection process, and (2) their algorithms required a lot of computational power which could not be used by drivers. Convolutional neural networks (CNN) provide an alternative method of automatically extracting and classifying features using deep learning (DL) methods.

III. EXISTING SYSTEM:

- Current pothole detection methods often rely on manual inspection or vibrationbased sensors installed in vehicles.
- Image processing techniques, such as edge detection and thresholding, have been used for detecting potholes in images.
- Some systems utilize accelerometers in vehicles to detect road irregularities, inferring the presence of potholes.
- Existing solutions may also involve crowd-sourced reporting, where drivers manually report potholes through mobile applications.

IV. PROPOSED SYSTEM

- The proposed system utilizes a CNN model to automatically detect potholes from live camera feeds and images in real-time.
- It leverages deep learning to learn complex features of potholes, improving detection accuracy compared to traditional methods.
- The system can be integrated with road monitoring infrastructure, enabling continuous and automated surveillance.
- It includes a notification mechanism to alert relevant authorities or road maintenance teams instantly upon detecting a pothole.

V. MODULE ADMIN MODULE

Dataset:

- The dataset consists of road images, including both images with potholes and images without potholes. It is crucial to have a diverse dataset that captures various lighting conditions, weather scenarios, and road types to ensure the model generalizes well.

- The images are collected from various sources, such as public datasets, and Kaggle website.

Preprocessing:

- Preprocessing involves resizing the images to a fixed size compatible with the VGG19 model, typically 224x224 pixels.
- Images are normalized by scaling pixel values to the range [0, 1] to improve model convergence during training.
- Data augmentation techniques such as rotation, zoom, and horizontal flipping are applied to increase the diversity of the training data, reducing the risk of overfitting.

Split Data:

- The dataset is split into three subsets: training, validation, and testing.

- A common split ratio is 70% for training, 15% for validation, and 15% for testing.

- The training set is used to train the model, the validation set is used to tune the model hyperparameters and avoid overfitting, and the test set is used to evaluate the final model's performance.

Train Data:

- VGG19, pre-trained on the ImageNet dataset, is used as the base model with the top layers removed.
- A new fully connected layer and a SoftMax output layer are added to the VGG19 base to classify images as containing potholes or not.
- The model is trained using the training data, with the validation set used to monitor its performance and adjust hyperparameters such as learning rate and batch size.

Accuracy Model:

- After training, the model's accuracy is evaluated on the test dataset.

- Accuracy, along with other metrics like precision, recall, and F1-score, is calculated to assess the model's effectiveness in detecting potholes.

- The model is fine-tuned, if necessary, by adjusting the training parameters or adding regularization techniques to improve accuracy.

Prediction:

- The trained model is used to predict whether an image or a frame from a live camera feed contains a pothole.
- The model outputs the probability of the presence of a pothole, and based on a threshold, it classifies the image accordingly.
- For real-time applications, the prediction pipeline is optimized for speed and accuracy, ensuring that the model can handle live camera input efficiently.

Flask Web App Integration (Live Camera Detection and Location Saving):

- A Flask web application is developed to integrate the trained model for live camera pothole detection.
- The web app captures live video feed from a connected camera, processes each frame, and applies the trained VGG19 model to detect potholes.
- Upon detecting a pothole, the app saves the frame, along with its location, to a csv file.

VI. ARCHITECTURE:

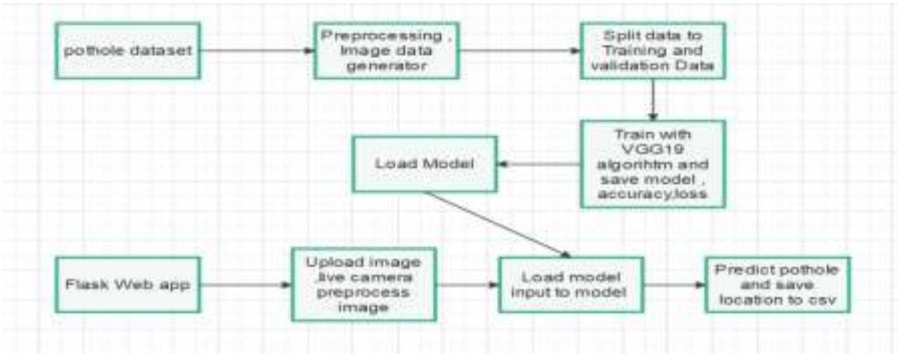

Figure 1. System Architecture

Figure 1 illustrates the framework of the proposed method and process of flow from loading dataset to prediction. Process of prediction is performed in two stages training stage and prediction stage. In training stage data is process through preprocessing data and split data in to training and validation and given input to VGG19 model and accuracy is calculated and model is saved in system. In second stage flask web application is designed where user can use live camera to predict pothole form live data.

VGG19 CNN algorithm:

VGG19 is a deep Convolutional Neural Network (CNN) architecture with 19 layers, designed for image classification and feature extraction. It uses small 3x3 convolution filters consistently across all layers, which helps in capturing fine details in images. VGG19 is known for its simple, uniform structure, and depth, which allows it to learn complex patterns. Despite its effectiveness, the model requires significant computational power and memory due to its large number of parameters. VGG19 has been widely used in various computer vision tasks and is a benchmark in the field.

Flow Diagram:

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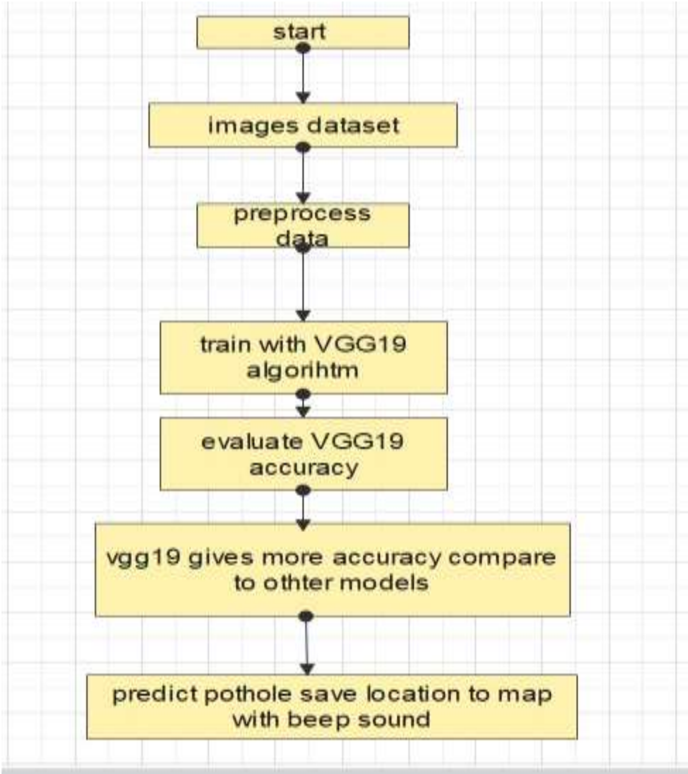


Figure 2. Model Flow Diagram

VII. EVALUATION METRICS

Loss and Accuracy Graphs

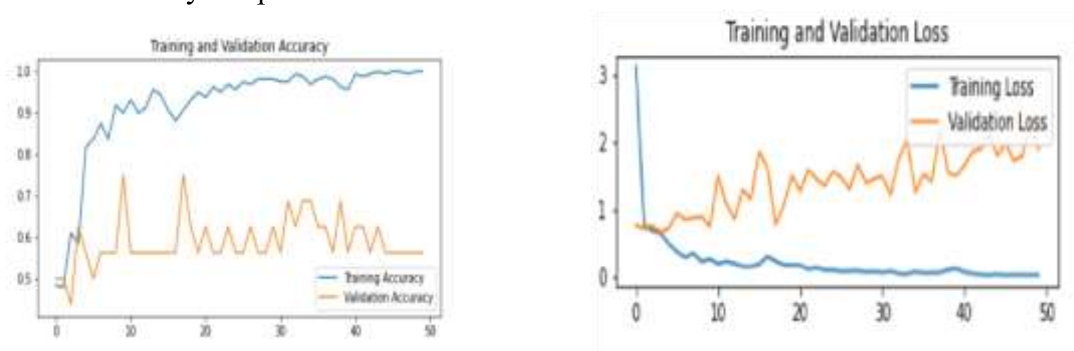


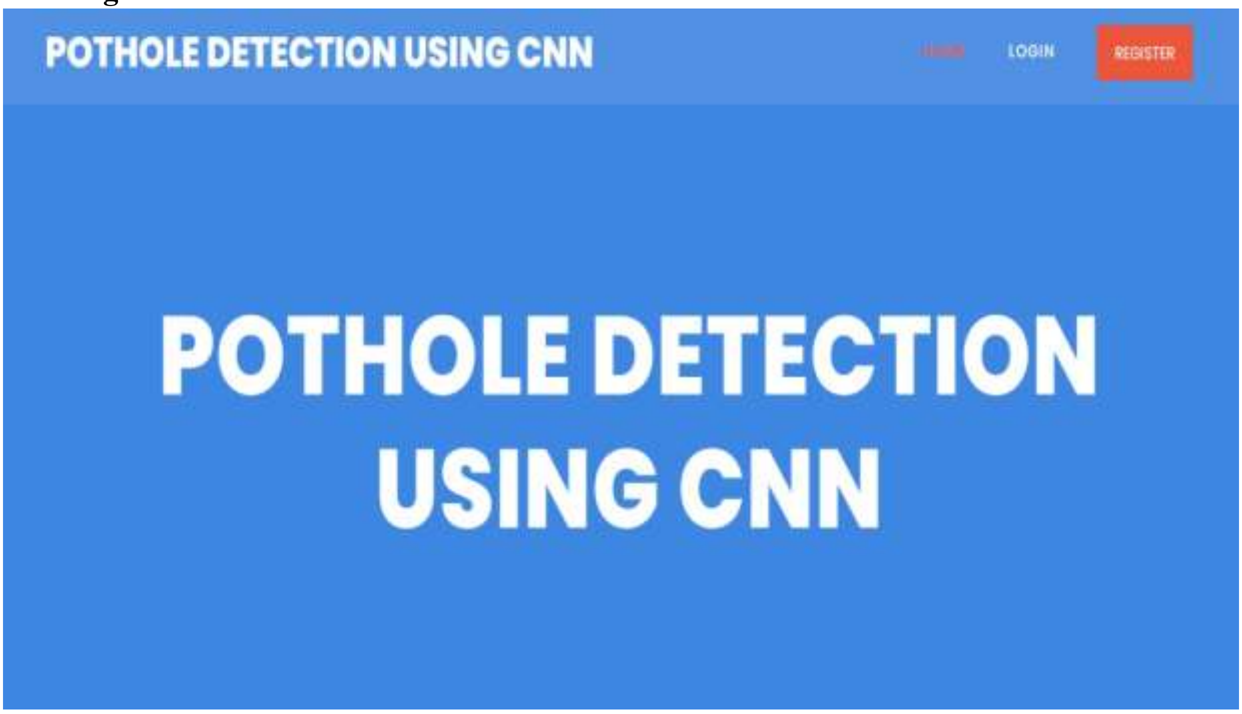
Figure 3: Training and Accuracy graph

Above graphs shows training and accuracy graphs for validation and training datasets. Training accuracy is 98 percent and validation accuracy are 70 percent.

VIII. RESULTS:

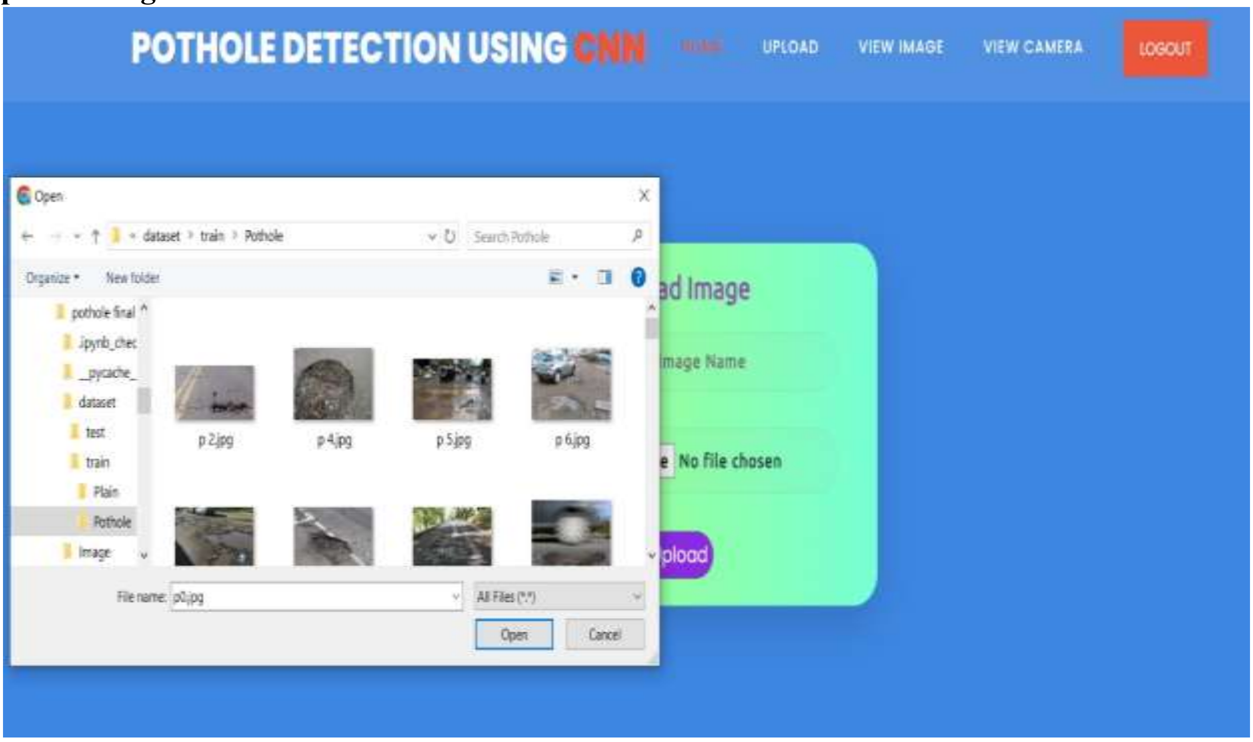
Dataset:

Home Page:



Input Form:

Upload Image:



Prediction Location:

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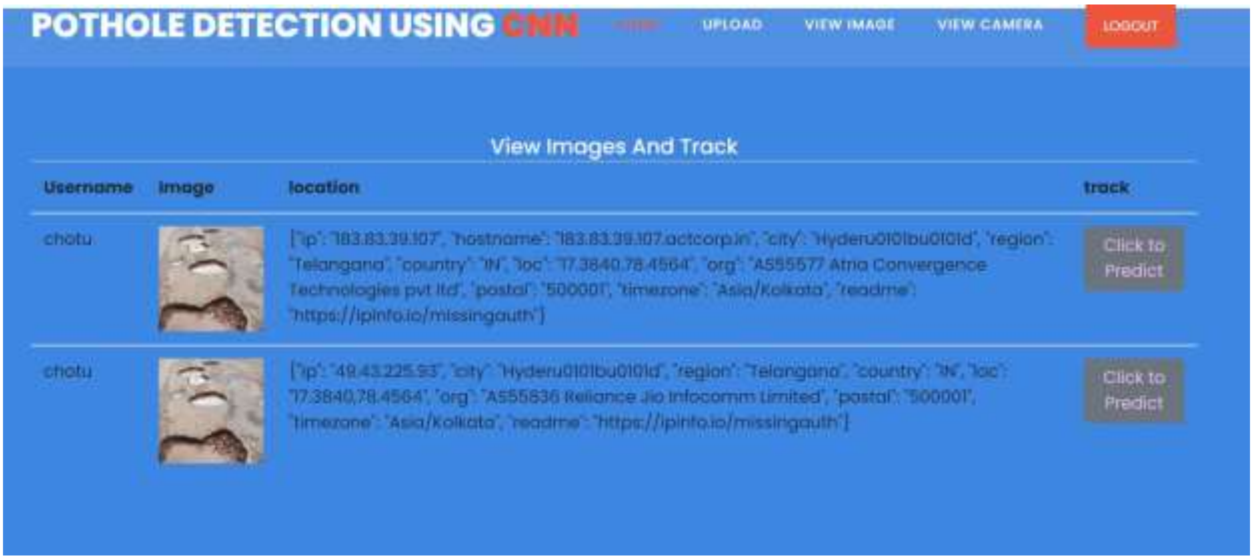

Result:

IX. CONCLUSION

The pothole detection system utilizing the VGG19 CNN architecture successfully identifies potholes in real-time from live camera feeds and images, demonstrating high accuracy and robustness across various road conditions. The integration with a Flask web app enables seamless deployment, allowing for immediate detection and location tracking of potholes, which can significantly enhance road maintenance efforts and improve safety. The system effectively reduces the reliance on manual inspections, offering a scalable solution for automated road monitoring. Due to its random size and shape, pothole detection is both essential and distinct from other detections such as automobiles, faces, etc. The research suggests doing a comparison analysis between sequential CNN, whereby CNN requires shorter training time while maintaining pothole detecting performance. Both photos and videos are subject to detection, with metrics of performance being tracked. Using a visionbased approach, the work may be improved to extract pothole properties like depth, and volume, etc.

X. FUTURE SCOPE

Future enhancements could include integrating additional sensors, such as LiDAR, to improve detection accuracy in adverse weather conditions.
The system could also be expanded to detect other road anomalies like cracks and road signs. Implementing edge computing could further reduce latency for real-time processing in smart city environments.
Additionally, the use of deep learning techniques, such as transfer learning with more advanced architectures, could further improve the model's performance. Finally, a mobile application could be developed for real-time alerts and reporting, making the system more accessible and user-friendly.

XI. REFERENCES

- D. E. Denning, ‘‘An intrusion-detection model,’’ IEEE Trans. Softw. Eng., vol. SE-13, no. 2, pp. 222–232, Feb. 1987.
- [2] N. B. Amor, S. Benferhat, and Z. Elouedi, ‘‘Naive Bayes vs decision trees in intrusion detection systems,’’ in Proc. ACM Symp. Appl. Comput. (SAC), 2004, pp. 420–424.
- [3] M. Panda and M. R. Patra, ‘‘Network intrusion detection using Naive Bayes,’’ Int. J. Comput. Sci. Netw. Secur., vol. 7, no. 12, pp. 258–263, 2007.
- [4] M. A. M. Hasan, M. Nasser, B. Pal, and S. Ahmad, ‘‘Support vector machine and random forest modeling for intrusion detection system (IDS),’’ J. Intell. Learn. Syst. Appl., vol. 6, no. 1, pp. 45–52, 2014.
- [5] N. Japkowicz, ‘‘The class imbalance problem: Significance and strategies,’’ in Proc. Int. Conf. Artif. Intell., vol. 56, 2000, pp. 111–117.
- [6] Y. LeCun, Y. Bengio, and G. Hinton, ‘‘Deep learning,’’ Nature, vol. 521, no. 7553, pp. 436–444, 2015.
- [7] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, ‘‘Deep learning for visual understanding: A review,’’ Neurocomputing, vol. 187, pp. 27–48, Apr. 2016.
- [8] T. Young, D. Hazarika, S. Poria, and E. Cambria, ‘‘Recent trends in deep learning based natural language processing [review article],’’ IEEE Comput. Intell. Mag., vol. 13, no. 3, pp. 55–75, Aug. 2018.
- [9] N. Shone, T. N. Ngoc, V. D. Phai, and Q. Shi, ‘‘A deep learning approach to network intrusion detection,’’ IEEE Trans. Emerg. Topics Comput. Intell., vol. 2, no. 1, pp. 41–50, Feb. 2018.
- [10] D. A. Cieslak, N. V. Chawla, and A. Striegel, ‘‘Combating imbalance in network intrusion datasets,’’ in Proc. IEEE Int. Conf. Granular Comput., May 2006, pp. 732–737.