Smart Elevator Obstruction Detection System using Image Classification

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***Abstract*—This paper proposes an approach that leverages real-time Image Classification to improve elevator safety. Elevators are a necessity for most multi story buildings. As a result, they play a crucial role in the lives of millions of people around the world. Despite this, there has been limited advancement in the technology used for elevator door operators. In the current system, elevators use multiple infrared transmitter/receiver pair of sensors to detect obstructions between the doors. This does not effectively detect smaller objects such as pets, small children, pet leashes etc. between the elevator doors which has led to thousands of tragic fatalities. This paper proposes an approach to tackle this challenge by leveraging Binary Image Classification to determine whether there is an obstruction between the elevator doors. This study includes the construction of a novel dataset of over 10,000 images and a comprehensive evaluation and comparison of several Machine Learning models for the proposed system. The results have produced novel findings that can be used to significantly improve safety and reliability of elevator door operators by preventing tragic fatalities every year.**

***Keywords*—Binary image classification; machine learning; deep learning; elevator safety**

I. Introduction

In today’s world, there are millions of multi-story buildings across the globe. Not only do elevators improve the convenience of vertical transportation, but they also play a vital role in providing accessibility for people with disabilities. It is clear that elevators have become a necessity in our daily life. It is estimated that the door operator works approximately 1.75 million times in 10 years [1].

In the early 2000s elevators were fitted with a retractable door edge such that if the elevator door came in contact with a person or obstruction while closing, the doors would stop closing. Modern elevator door operators use non-contact detection device which includes a photoelectric detection device, ultrasound monitoring device, red light curtain detector, electro-magnetic induction detector, and other inputs to detect obstructions between the doors [2]. However, many cases have shown that such technology has limitations when detecting small obstructions such as leashes, pets or children [3]. Because of this inefficiency, there are thousands of fatalities every year. Despite the widespread use of this elevator technology and the serious consequences of its inefficiencies, there has been limited research on the technology used for elevator door controllers. Although there has been growing interest in developing Smart Buildings and Smart Cities, elevator door control remains an underexplored research area. There is a large scope to use modern techniques from computer vision and artificial intelligence to improve the existing elevator door control technology in a cost-effective manner. Widespread implementation of such improved systems has the potential to save lives and prevent injuries. This paper seeks to tackle the aforementioned challenge of improving the reliability and efficiency of elevator door operators.

Machine learning and image classification techniques – to the best of our knowledge – have not yet been used to address the challenge of improving the safety and reliability of elevator door operators.

The contribution of this paper is to:

- Propose a system that leverages machine learning and image classification techniques to overcome the shortcomings of existing elevator door control operators.
- Construct a novel dataset of over 10,000 images which serve as input to the proposed system. The images are captured by simulating the 8 positions along the top and sides of the elevator car door. Brightness augmentation is performed to improve the robustness of the system in different daylight conditions.
- Evaluate and compare the speed and efficacy of several machine learning models, namely Linear SVC, k-NN, Decision Tree, Random Forest, and CNN.
- Identify the most suitable classifiers for the proposed system based on the results of this study.
- Assess the feasibility of the proposed system based on the results of this study.

This paper proposes an approach to address the problem of elevator door operator obstruction detection to improve safety of the passengers entering and exiting the elevator in real-time.

The following section describes related research works followed by a description of the materials and methods. This includes details regarding the dataset construction, proposed system, models considered and evaluation metrics. Then the results of the study are presented. This is followed by the conclusion and future scope of the paper.

II. Related Work

In "Discussion on Improving Safety in Elevator Management", [4] Feng ShuanChang et al. discuss the need to improve elevator technology given its direct relation to people's lives. The authors also elaborate on the complexity of the elevator user unit and the lack of ownership for elevator maintenance among stakeholders which often leads to neglect of elevator safety.

Magota et al. [5] improve the opening-and-closing speed control of the elevator doors using ILQ design method with frequency shaping. The authors focused on developing a smoother and quicker elevator door control system rather than addressing the challenge of efficient obstruction detection.

Zeng et al. [6] propose the use of the atmega32 control chip and ov7620 image acquisition chip to tackle this challenge. The authors adopt an image processing-based approach by implementing Semi-Neighborhood Averaging Algorithm and Background Difference Method on the image pixels to identify the moving obstruction.

Various systems have been proposed in existing literature to predict the failure of elevators based on knowledge graphs [7] and neural networks [8]. Yanbin Guo et al. [9] propose a system to monitor the elevator for the most common faults based on multi-sensor fusion. This system includes a web client to view the live reports of the system and a camera to monitor the passengers inside the elevator car.

Amruthnath and Gupta [10] research the use of unsupervised machine learning algorithms, such as hierarchical clustering, k-means and fuzzy c-means, for predictive maintenance of elevators.

In "Machine Learning Modelling for Failure Detection of Elevator Doors by Three-Dimensional Video Monitoring" [11] Chih-Yu Hsu et al. propose a method for detection of elevator failure by using three-dimensional video monitoring. This method involves extracting the signal from the dynamic distances between elevator doors and modelling by trapezoidal curves. The failure detection is done by identifying these dynamical signal curves of the elevator doors using trained classifiers.

Wan et al. [12] study the use of least square support vector machine for diagnosing elevator various malfunctions using vibration signals from the elevator functions. The authors optimize the parameters of LS-SVM using K-fold cross validation.

Mishra and Huhtala [13] propose an algorithm to extract highly information features from the elevator data which is used to improve fault detection. This algorithm uses profile extraction and deep autoencoder feature extraction on the dataset.

The use of big data for fault warning of the elevator system has also been explored [14] [15]. Ming Zihan et al. [16] propose an alternate method for monitoring the elevator system by leveraging IoT.

Olalere and Dewa [17] employ a remote condition monitoring (RCM) approach for proactive maintenance of elevators. This approach uses vibration and machine-room temperature data acquired through IoT devices. Systems to protect passengers from the accidental movement of the elevator car have also been proposed in previous research [18] [19].

With the prevalence of big data, data mining technology and artificial intelligence have shown great promise in detecting the failure and evaluating the risk of elevators [20]. Wang et al. [21] study the use of Hadoop to design the data mining and analysis platform. The authors also use Hadoop to improve and parallelize the K-means and Apriori algorithms to mine the massive amounts of data from the elevator monitoring database.

A majority of existing research investigates the use of modern technology to improve maintenance of the elevator by remotely monitoring the overall elevator system for signs of faulty behavior or damage. However, related works do not address the shortcomings of existing elevator technology in effectively detecting obstructions between the doors.

In this paper, we tackle the aforementioned shortcomings by proposing a novel approach that leverages binary image classification to efficiently detect obstructions between the elevator doors. An image dataset of over 10,000 images was constructed to simulate the working of the proposed system. Several image classifiers were built, evaluated and compared on both the augmented and original image datasets.

III. Materials and Methods

A. Dataset

The dataset was collected by simulating the 8 camera positions, as shown in Fig. 1, using a functional elevator in a multi-story building. This consisted of two cameras positioned at the top view of the elevator and 3 cameras at equidistant positions along each elevator car door. Each camera recorded videos of the various obstructions passing through the elevator car doors. Every fifth frame was extracted from the videos to compile the image dataset. The code to perform this frame extraction is displayed in Fig. 2. Each image was manually labelled as either 'Obstruction' or 'No Obstruction'.

Brightness augmentation was performed on the images to simulate various lighting conditions. Thereby, improving the robustness of the obstruction detection at different hours during the day. Each image was augmented using 12 different brightness factors ranging from 0.5 to 1.6 as shown in Fig. 3. The code used to perform augmentation is displayed in Fig. 4. Grayscale augmentation was also explored however it had minimal effect on the performance of the binary image classification models. The images were divided into two datasets, namely side view images and top view images. A sample of the side view and top view images are shown in Fig. 5 and 6 respectively. The images captured have a size of 1,280 x 720 pixels as well as a horizontal and vertical resolution of 96 dpi. Each dataset is fairly balanced, as shown in Table I. The total size of both datasets together is 10,836 images.

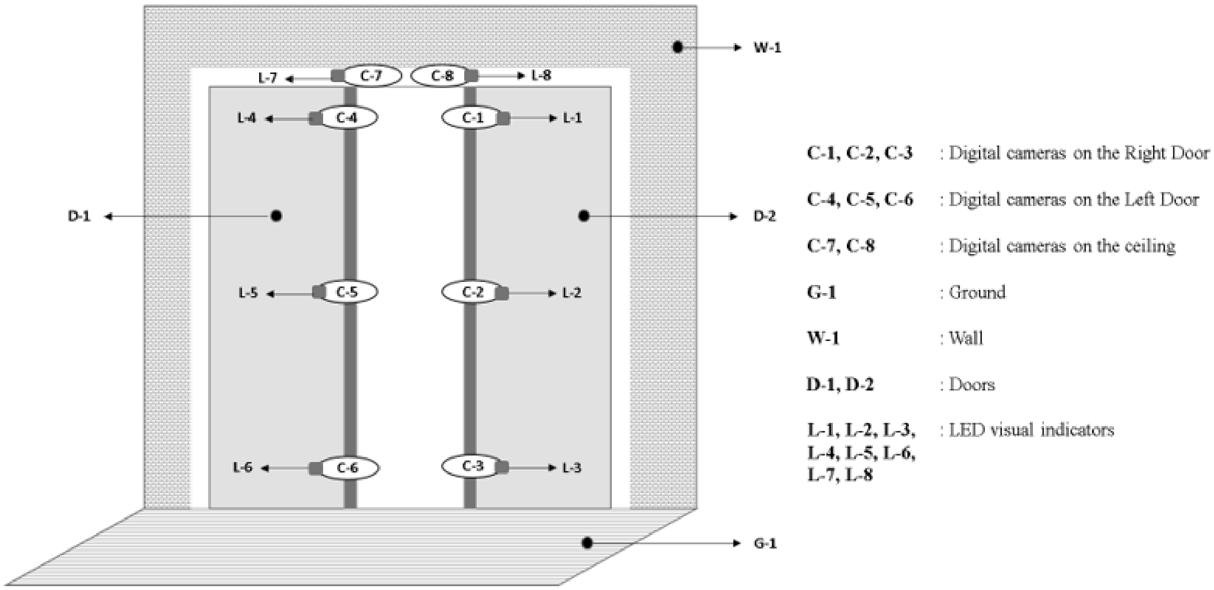

Fig. 1. Positioning of the Cameras and LEDs in the Proposed System.

```
vidcap = cv2.VideoCapture('Video.mp4')
success,image = vidcap.read()
count = 0
while success:
 if count%5==0:
 cv2.imwrite("Data Collection\\Video\\frame_%d.jpg" % count, image)
 success,image = vidcap.read()
 print('Read a new frame: ', success)
 count += 1
```

Fig. 2. Code Extracting Every Fifth Frame from a Video.

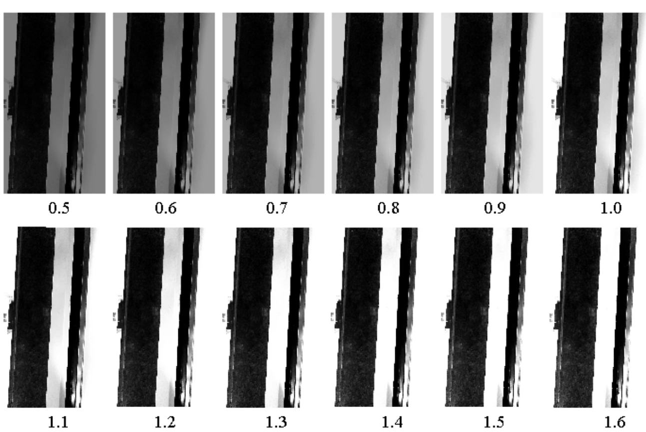

Fig. 3. Twelve levels of Brightness Augmentation used on the Dataset.

```
All_files=os.listdir(InDir_path)
for curr_fileName in All_files:
 full_in_file_name = InDir_path+"\\"+curr_fileName
 curr_length = len(curr_fileName)
 part_1=curr_fileName[0:(curr_length-4)]
 part_2=curr_fileName[(curr_length-4):99]

 try:
 im=Image.open(full_in_file_name)
 enhancer = ImageEnhance.Brightness(im)
 factorList=[0.5,0.6,0.7,0.8,0.9,1,1.1,1.2,1.3,1.4,1.5,1.6]
 counter=0
 for factor in factorList:
  im_output = enhancer.enhance(factor)
  full_out_file_name =
OutDir_path+"\\"+part_1+"_"+str(counter)+part_2
  im_output.save(full_out_file_name,"JPEG")
  counter=counter+1
 except IOError:
 print("cannot process file",full_out_file_name)
```

Fig. 4. Code to Perform Brightness Augmentation.

B. Proposed System

The elevator car carries riders between the floors of a multi-story building by moving up and down in the elevator shaft. Most elevators are automatic and do not have any personnel present to operate the elevator. Elevators have two doors, one fixed to the frame, mounted on the wall and one attached to the elevator car. When the elevator reaches the destination floor and parks, both of these doors open synchronously.

Fig. 5. Sample Side View Image.

Fig. 6. Sample Top View Image.

TABLE I. IMAGE DISTRIBUTION IN THE DATASET

View	Label	Number of Images
Side View	No Obstruction	4,128
Side View	Obstruction	3,204
Top View	No Obstruction	1,848
Top View	Obstruction	1,656

The proposed obstruction detection system will use 8 digital cameras as input devices. This includes three cameras mounted along each side of the elevator car door and two cameras mounted at the top of the elevator frame. Using multiple cameras located at various positions provides different views/perspectives of the obstruction passing through the elevator doors. This improves the effectiveness of the proposed system for detecting small or narrow objects which is a significant advantage over existing elevator door control technologies.

These cameras will capture images periodically every few milliseconds. These images are processed by the hardware and software system mounted in the elevator cars. Each image is passed to a pre-trained image classifier. The pre-trained model will perform binary image classification to determine whether there is an obstruction between the elevator doors. The proposed system will have two separate models for top view classification and side view classification respectively. By leveraging binary image classification using machine learning and deep learning, the proposed system will be able to detect obstructions with high accuracies in real-time.

If an obstruction is detected, then the signaling mechanism is triggered and a signal will be sent to the door controller to stop and reverse. Each camera has an LED light fastened next to it. If an obstruction is detected one of the images captured, the light next to the corresponding camera will turn on to notify the passengers about where the obstruction is detected. This also helps simplify the maintenance of the proposed system. If there is no obstruction detected, then the closing process will continue. The system continues to monitor for any obstructions until the gap between the elevator doors is too small to capture a digital picture. The methodology of the proposed system is illustrated in Fig. 7.

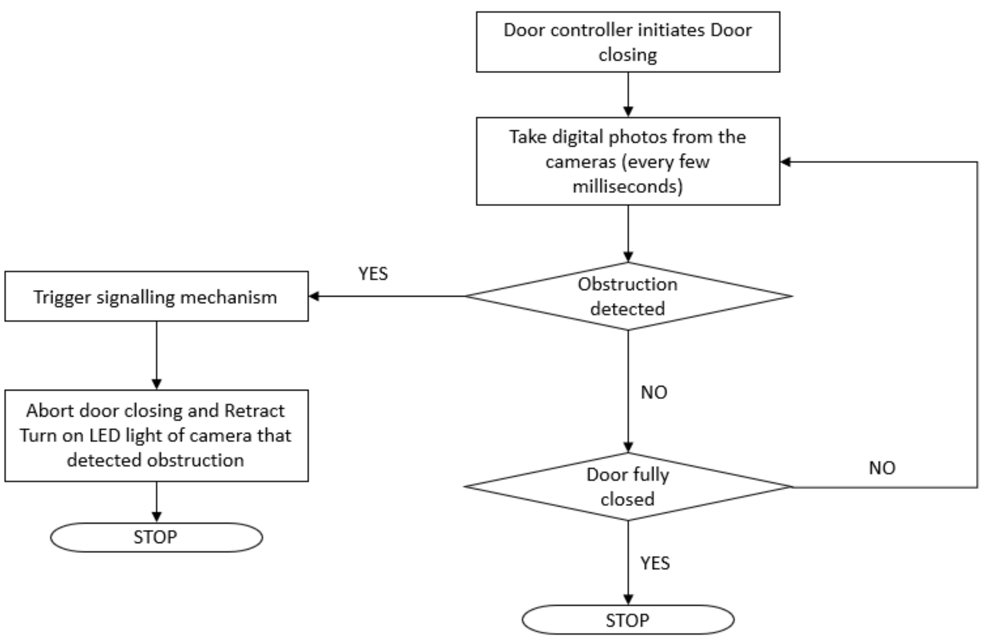

Fig. 7. Methodology of Proposed Elevator Obstruction Detection System.

C. Models

Several machine learning and deep learning models were built and evaluated to determine the most suitable model for the proposed system. These classifiers were chosen based on their ease of use, solid performance, and popularity in related works which leverage binary image classification for real-world applications.

1) Linear SVC: Linear Support Vector Classifier (SVC) is a supervised machine learning algorithm. It can be used for both regression and classification challenges. In this paper, Linear SVC is used for image classification. The data points are plotted in the n-dimensional space and the algorithm identifies the best fit hyperplane which divides the data into categories.

2) k-NN: The k-Nearest Neighbours (k-NN) classifier has proven to be an effective classification model on numerous occasions. This model uses the labelled training data to predict the output. The predicted value is determined as the majority in the 'k' nearest neighbours. For the k-NN classifiers in this paper, k=3.

3) Decision Tree: Decision Tree (DT) is an algorithm which has a flowchart-like tree structure. The leaves of the tree represent the target or outcome variables. In this case, the leaves can take the value 'Obstruction' or 'No Obstruction'. The decision tree classifiers implemented in this paper have a depth of 3.

4) Random forest: Random forest is a combination of multiple tree classifiers where each tree is based on independently sampled random vector values. Since it consists of multiple trees, it is called a forest. While this algorithm requires more computational power and time than decision trees, it helps improve the accuracy and reduce overfitting.

5) CNN: Convolutional neural network (CNN) is a type of deep learning algorithm which establishes learnable biases and weights to various aspects in an input image in order to differentiate one from another. The CNNs implemented in this paper have the classic architecture as a Sequential model with Convolution layers, Pooling layers and ReLU layers.

D. Evaluation

The speed and correctness of the predictions made by the classifier are crucial to determine which models would be suitable for the proposed system. The computation time of each model for test data prediction was calculated in seconds. Various metrics, namely accuracy, precision, recall and F1 score, were used to evaluate and compare the performance of the models.

In this paper, the binary classification task is defined such that each image is classified as either 'No obstruction' or 'Obstruction'. The True Positive (TP) attribute of the confusion matrix is defined as the number of images which contain an obstruction and were classified as 'Obstruction' by the model. Similarly True Negative (TN) is the number of images which contain no obstructions and were classified as 'No obstruction', False Positive (FP) is the number of images which contain no obstructions but were incorrectly classified as 'Obstruction and False Negative (FN) is the number of images which contain obstructions but were incorrectly classified as 'No obstruction'

These confusion matrix metrics were used to calculate accuracy, precision, recall and F1 score. Accuracy is the number of correctly classified images over the total number of images. Accuracy is calculated using all four of the aforementioned components of a confusion matrix (1).

$$\text{Accuracy} = \frac{TN+TP}{TN+FP+TP+FN} \quad (1)$$

Precision is the ratio of true positives to all positives. It gives greater importance to false positives. A precision value closer to 1 indicates that the model is performing well. Precision is calculated using the True Positive and False Positive attributes. (2).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall is a very important evaluation metric for the proposed system because it assigns more weightage to false negatives. A false negative in the proposed system means that the obstruction is present but it is not detected by the model. As a result, the doors will close normally and the person may be injured. Thus, it is crucial to minimize the number of false negatives. Recall is calculated using the True Positive and False Negative attributes. (3).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

F1 score is defined as the weighted average of precision and recall (4). If the F1 score is closer to 1, it indicates that the classifier has performed well.

$$\text{F1 score} = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

The models were built and evaluated separately for top view image classification and side view image classification.

IV. Result and Discussion

The models and algorithms elaborated in the previous section were implemented and compared. Table II provides a detailed summary of the performances of each model for top view image classification. It can be seen that the k-NN model performed the best out of all the classifiers with an F1 score of 0.994 and accuracy of 99.8%. This was followed closely by the CNN model which had an accuracy of 98.9%. Among the models implemented on the original image dataset, both the Linear SVC and Random Forest models performed remarkably well with the same accuracy of 98.6%. All of models performed well with respect to the considered evaluation metrics.

Table III provides a detailed summary of the performances of each model for side view image classification. It can be seen that the k-NN and CNN models performed the best with accuracies of 99.8% and 99.3% respectively. Among the models implemented on the original dataset, k-NN performed the best with an accuracy of 95.4%.

TABLE II. MODEL EVALUATION AND COMPARISON FOR TOP VIEW CLASSIFICATION

Model Name	Dataset	Accuracy	Precision	Recall	F1 Score
Linear SVC	Top View images (Original)	0.986	0.99	0.98	0.99
k-NN	Top View images (Original)	0.973	0.98	0.97	0.97
Decision Tree	Top View images (Original)	0.945	0.94	0.94	0.94
Random Forest	Top View images (Original)	0.986	0.99	0.98	0.99
Linear SVC	Top View images (Augmented)	0.967	0.97	0.96	0.97
k-NN	Top View images (Augmented)	0.998	1.00	0.99	0.994
Decision Tree	Top View images (Augmented)	0.957	0.96	0.96	0.96
Random Forest	Top View images (Augmented)	0.977	0.98	0.98	0.98
Model Name	**Dataset**	**Accuracy**			
CNN	Top View images (Augmented)	0.98.9			

TABLE III. MODEL EVALUATION AND COMPARISON FOR SIDE VIEW CLASSIFICATION

Model Name	Dataset	Accuracy	Precision	Recall	F1 Score
Linear SVC	Side View images (Original)	0.93	0.94	0.92	0.93
k-NN	Side View images (Original)	0.954	0.96	0.95	0.95
Decision Tree	Side View images (Original)	0.797	0.84	0.78	0.78
Random Forest	Side View images (Original)	0.856	0.90	0.84	0.85
Linear SVC	Side View images (Augmented)	0.967	0.97	0.96	0.97
k-NN	Side View images (Augmented)	0.998	1.00	0.997	0.998
Decision Tree	Side View images (Augmented)	0.859	0.88	0.85	0.85
Random Forest	Side View images (Augmented)	0.889	0.91	0.88	0.88
Model Name	**Dataset**	**Accuracy**			
CNN	Side View images (Augmented)	0.993			

The speed of each classifier was evaluated and compared in seconds as shown in Fig. 8 to 11. The speed is the computation time for classifying the test data. This is an important metric for the proposed system since the classifier must be able to identify whether or not an obstruction is present in the captured image in real-time. The computation times of the models were measured for top view classification and side view classification separately. Top view classification refers to classifying the images captured by the two cameras positioned at the top of the elevator. Side view classification refers to classifying the images captured by the 6 cameras positioned along the sides of the elevator car door. The speed of each model was also measured separately for the original dataset and augmented dataset. It can be seen that the Decision Tree model consistently performed with the lowest computation time followed by the Random Forest model. However, there is a trade-off between speed and correctness of predictions as the Decision Tree classifier had the poorest accuracy among the models considered.

In this study, a novel system design which leverages state-of-the-art machine learning techniques to detect obstructions between elevator car doors is proposed. Furthermore, an end-to-end analysis of its feasibility is presented which includes construction of a dataset of over 10,000 images, implementation of several modern binary image classifiers, and a thorough evaluation of model performances. This work advances the literature on improving elevator safety. The proposed system is designed to address the shortcomings of current elevator technology [2] by facilitating more effective detection of small and narrow obstructions through real-time image input. The use of machine learning techniques for elevator door control is – to the best of our knowledge – new. In contrast, a majority of existing works on improving elevator safety focus on detecting [9] [13] [14] [15] [20] and predicting [7] [8] elevator failure. Certain studies [6] focus on detecting only moving obstructions between elevator car doors whereas, the proposed system facilitates the detection of both moving and stationary obstructions.

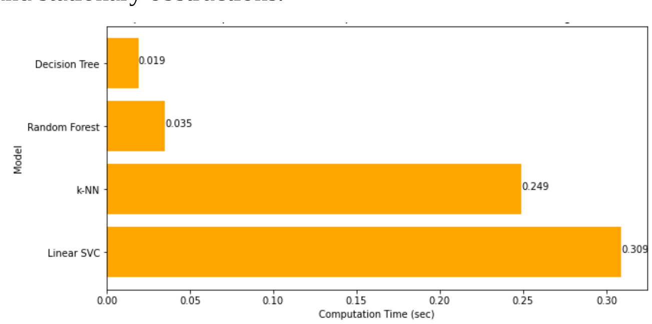

Fig. 8. Comparison of Computation Times for Top View Classification of Test Data (Original Dataset).

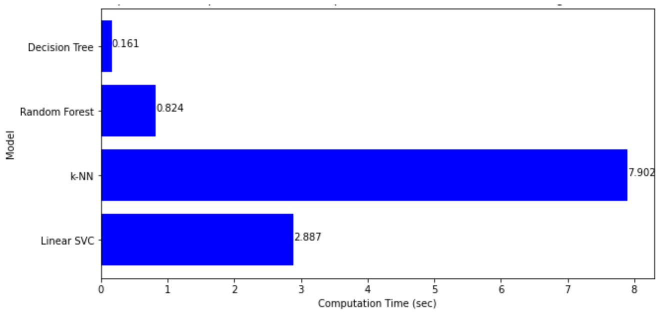

Fig. 9. Comparison of Computation Times for Top View Classification of Test Data (Augmented Dataset).

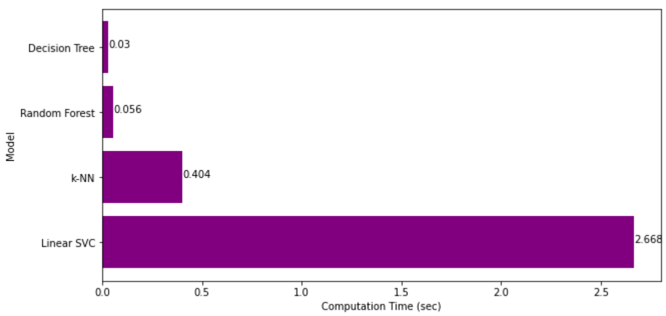

Fig. 10. Comparison of Computation Times for Side View Classification of Test Data (Original Dataset).

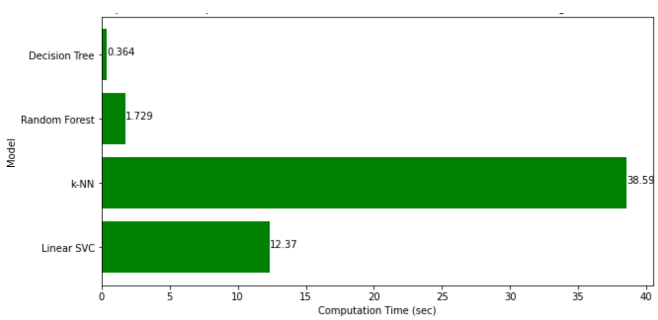

Fig. 11. Comparison of Computation Times for Side View Classification of Test Data (Augmented Dataset).

V. Conclusion and Future Work

Despite the widespread interest in the development of Smart Cities and Smart Buildings, very little advancement has been made in the technology used for elevator door operators. This paper proposes a novel elevator obstruction detection system that leverages modern technology such as binary image classification models, to improve the safety of elevators by effectively detecting smaller or narrower obstructions. This paper presents findings based on the evaluation and comparison of different binary image classification techniques for the purpose of obstruction detection. The considered models include Linear SVC, k-NN, Decision Tree, Random Forest, and CNN. A dataset was created through simulation of the proposed system using a functional elevator in a multi-story building. Brightness augmentation was used to improve the robustness of the models in different lighting conditions. The results of this paper show that it is feasible to develop the necessary models to perform image classification for the proposed system with high accuracies in real-time. All of the models performed well with respect to the considered evaluation metrics. The k-NN and CNN models had the highest accuracies for both datasets. However, the k-NN model had one of the highest computation times, indicating that the CNN model may be more suitable for the proposed system. While the Decision Tree model had the lowest computation time, this model also resulted in the lowest accuracy when compared with the performances of the other classifiers considered.

The work presented in this study can be extended to include the storage of the images captured to further improve the performance of the model. The use of different machine learning and image processing algorithms can be explored. Additional data can be collected to increase the size and improve the quality of the dataset.

Improving the safety and reliability of elevators presents itself as an underexplored research area with the potential to have a positive impact on millions of lives around the world. With the continuous advancement in the field of machine learning, computer vision and artificial intelligence, the scope of this paper is vast. The results of this paper can be used to improve the safety of elevators by leveraging the efficacy and immense capabilities of modern technology.

Acknowledgment

The authors would like to thank the institution Vellore Institute of Technology, Chennai for its constant support and for providing a conducive learning environment.

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