Enhancing the Theft Detection of Vehicle and Emergency Alert Using Novel ResNet -50 over K-Nearest Neighbors Classifier

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- Keywords: Vehicle Theft Detection, Machine Learning, Novel ResNet -50, K-Nearest Neighbors, Facial Recognition, Biometric Recognition, Theft.
- Abstract: This study seeks to bolster the security of vehicles in public car parks by advancing automated vehicle theft detection using two unique machine learning methods. We've opted for the Novel Resnet-50 and K-Nearest Neighbours classifiers. Their performance was assessed to gauge their proficiency in vehicle theft detection. With 80% of the dataset used for training and the remaining 20% for testing, using a sample size of ten, the performance of the Novel Resnet-50, which utilises facial recognition to enhance vehicle safety, was pitted against K-Nearest Neighbours. The former posted an impressive 97% accuracy, showcasing its prowess in spotting unauthorised users, while the latter recorded a 94% accuracy, with a significance level of 0.005 (p<0.05). Evidently, the Novel Resnet-50's integration of facial recognition offers a promising avenue in vehicle security enhancement compared to K-Nearest Neighbours.

1 INTRODUCTION

The video footage captured by surveillance cameras located in public areas such as parks, car parks, shops, and homes is manually reviewed to pinpoint missing objects (Bosire and Maingi 2021). This timeconsuming procedure requires considerable manpower, especially challenging given the 24/7nature of live streams. As a result, machinery was introduced to handle video surveillance. Many researchers advocate for embedded systems for this analytical task. While these systems utilise various sensors to detect robberies, they fall short in identifying the thief and notifying the rightful authorities. The advent of IoT addressed this gap, enhancing analytical functionality. Recent research focusing on facial recognition suggests employing data mining to streamline the process, given the array of available ML methodologies. This research employs Machine Learning to bolster the accuracy of human identification in processed images (B, Pranav, and Manikandan 2020a). Such applications span from fake voter detection, credit card fraud mitigation, to crop disease prediction (Johri, Verma, and Paul 2020).

Between 2006 and 2023, a total of 2350 articles were reviewed, with 450 sourced from IEEE Xplore, 1000 from ResearchGate, 700 from Elsevier, and 200 from Springer. These articles endorsed the acoustic intruder approach to fortify domestic security systems. They evaluated changes in room acoustic transfer function features to identify intruders. The robust system they developed classifies voters' eligibility, relying on biometrics for authentication (BalaMurali, Sravanthi, and Rupa 2020). The repeated line tracking algorithm, proposed by (Hashimoto, n.d.), aims to refine finger vein recognition. For bolstering secure smart voting, voters' photographs and fingerprints are collated (Arputhamoni and Saravanan 2021). Before participating, two-factor authentication is conducted. CNN serves as the classifier in this approach. A biometric scanner discerns between registered and unregistered voters, making this system both reliable and somewhat time-intensive (Ibrahim et al. 2021).

Presently, Machine Learning stands as the predominant method for rapidly devising solutions to complex problems. The proposed system amalgamates ML classifiers with facial recognition technology to differentiate between authorised and

415

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DOI: 10.5220/0012505300003739

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In Proceedings of the 1st International Conference on Artificial Intelligence for Internet of Things: Accelerating Innovation in Industry and Consumer Electronics (AI4IoT 2023), pages 415-422 ISBN: 978-989-758-661-3

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Subash, G. and Kalaiarasi, S.

unauthorised users. The paramount goal is to elevate recognition accuracy, even when handling subpar image quality.

2 MATERIALS AND METHODS

This research took place in the computer centre of Saveetha School of Engineering, within the Saveetha Institute of Medical and Technical Sciences. The study utilised 20 samples and implemented the classifiers Novel Resnet-50 (Liu et al. 2021) and KNN (Chanal et al. 2022). Python compiler was used for the automated vehicle theft detection and prevention. For the statistical evaluation of this experiment, IBM SPSS software, version 26, was employed.

2.1 Novel Resnet -50

The classifier known as Novel Resnet-50 is a type of CNN that employs a residual learning framework and jump connections (Liu, 2021). It features multiple convolutional blocks, five convolutional layers, and incorporates average pooling. For the purpose of classification, a Softmax layer is utilised. To link with the preceding layer, skip connections are used. Within these skip connections, a neural network is implemented to boost accuracy, and the model exhibits two mappings.

2.1.1 Pseudocode

Step 1: First step involves gathering the necessary amount of data for the project.

Step 2: In the next stage, the data undergoes preprocessing.

Step 3: Any noise or empty spaces present in the data are removed for further processing.

Step 4: The classification model is then developed and trained.

Step 5: Finally, the data is classified with the desired accuracy level.

2.2 K-Nearest Neighbours

The simplest ML classifier is based on the supervised learning approach. This non-parametric method is predominantly employed for classification tasks. Known data are preserved under selected features and used to compare the classes of the K-nearest data points to determine the class of new data. This method is especially popular for training with large datasets. It's often utilised for constructing graphs (Chanal et al. 2022).

2.2.1 Pseudocode

Step 1: Load the selected dataset into the network for processing.

Step 2: Modify the dataset by pre-processing and cleaning techniques to eliminate any inconsistencies or inaccuracies.

Step 3: Choose the relevant attributes from the dataset and extract the necessary features required for improving the classification accuracy.

Step 4: Train the classification model using the selected features, utilizing suitable ML algorithms and techniques.

Step 5: Conduct the classification process on the trained model using the remaining data, and analyse the results to determine the accuracy of the model.

3 STATISTICAL ANALYSIS

This research utilised the Statistical Analysis Program, often referred to as SPSS, for data analysis. The independent variable under consideration was the image of the number plate, captured for verification. Meanwhile, the dependent variable was the representation of numbers and letters from the number plate image, illustrated through bar graphs. The study undertook ten iterations for each group, noting the anticipated accuracy for data assessment. An independent sample T-test was executed to ascertain the significance between the two groups.

4 RESULT

The effort to enhance the security system of vehicles parked in public spaces like hotels, parking lots, streets, and resorts involved analysing and implementing automated vehicle theft detection. This was achieved using classifiers, specifically the Novel Resnet -50 and KNN. Utilising the Python compiler, the Novel Resnet -50 and SGD achieved accuracies of 97% and 94%, respectively. The proposed Novel Resnet -50 classifier notably detected fraudulent activities concerning parked vehicles. The calibre of these classifiers was evident in their performance metrics. Figure 1 and Figure 2 illustrate the Confusion Matrix of both KNN and ResNet50. Meanwhile, Figure 3 displays the Training and Testing accuracy of ResNet, with Figure 4 showing its Training and Testing Loss. Table 1 lists the accuracy gains of the Novel Resnet -50 and GoogleNet classifier from ten separate instances using the Python compiler. The

vehicle licence plate's detection and character segmentation during testing are depicted in Figure 5, with the segmented characters and their predicted values presented in Figure 6. A comparison of accuracies between GoogleNet and ResNet-50 is seen in Figure 7. Finally, the performance metrics of the current and proposed models, evaluated on the grounds of specificity and sensitivity, are portrayed in Figure 8 (specificity) and Figure 9 (sensitivity).



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Figure 6: Segmented characters and their predicted value.







Figure 8: Specificity comparison between KNN and ResNet-50.



Figure 9: Sensitivity comparison between KNN and ResNet-50.

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Error Bars: +/- 1 SD

Figure 10: Mean accuracy comparison of ResNet-50 and KNN on real-time vehicle theft detection and improving the security system by facial recognition. The proposed method attained a mean accuracy of 97.3500%, which is greater than the conventional method of 93.6220%. X-axis represents accuracy of ResNet-50 and KNN; Y-axis represents mean accuracy \pm 1SD.

Table 1: Performance Metrics between Existing and Proposed model.

Model	Accuracy	Specificity	Sensitivity	
KNN	94%	0.97	0.93	
ResNet	97%	0.99	0.98	

Table 2: Accuracy comparison of Conventional and Proposed method.

SCIENCE AND TEC	Accuracy (%)
ResNet-50	KNN
94.51	90.62
94.80	91.37
95.37	92.88
96.99	93.17
97.11	93.43
97.58	94.00
98.85	95.91
99	96.53
99.37	96.99
99.92	97.81

Table 3: The mean and standard deviation of the group and accuracy of the ResNet-50 and SGD algorithms were 97.3500% and 1.95466, 94.2710% and 2.43539, respectively. In comparison to the KNN, ResNet-50 had a lower standard error of 0.61812.

Group Statistics							
	GROUP NAME	Ν	Mean	Standard Deviation	Standard Error Mean		
A	ResNet-50	10	97.3500	1.95466	.61812		
Accuracy	KNN	10	94.2710	2.43539	.77014		

Independent Sample Test										
Levene's Test for Equality of Variances			T-test for Equality of Means							
		F	F Sig.	Т	T Df	Sig. (2- tailed)	Mean Difference	Std. Error Differenc	95% Confidence Interval of the Difference	
							es	Lower	Upper	
Accuracy	Equal Variances assumed	.815	.378	3.118	18	.005	3.07900	.98751	1.00431	5.15369
	Equal Variances not assumed			3.118	17.195	.005	3.07900	.98751	.99732	5.16068

Table 4: The independent sample test revealed a substantial variation in accuracy among the suggested ResNet-50 and KNN classifiers. Since p<0.05, it is statistically significant.

5 DISCUSSION

Performance analysis using the KNN and ResNet Model yielded impressive results, with mean accuracies of 97% and 94% respectively. According to our experimental findings, the proposed system stands out as the optimal solution for facial recognition-based vehicle theft detection and promptly alerting the rightful owners.

This research utilised face recognition on the AT&T dataset as well as real-time inputs, achieving system accuracies of 98.75% for the chosen dataset and 98% for real-time inputs (B, Pranav, and Manikandan 2020a). Another study by (B, Pranav, and Manikandan 2020b) employed a CNN for facial recognition on two distinct datasets - AT&T and Ysale, with resultant accuracies of 100% and 96%, respectively. Additionally, (Yu et al. 2022) introduced two distinct machine learning classifiers for facial recognition, achieving a live facial recognition accuracy of 97% with GoogleNet-M. They subsequently integrated regularization and migration learning techniques, boosting the accuracy to 98%. In a comparison of the proposed DCNN classifier with SVM, KNN, and DT, an impressive accuracy rate of 99% was achieved (AbdELminaam et al. 2020).

However, shallow networks often suffer from suboptimal learning capabilities, making error identification a challenging task. Future improvements might come from employing a vast dataset, exploring a myriad of techniques beyond just neural networks, and adopting filtering approaches. For future research, a rapidly trainable classifier is suggested.

6 CONCLUSION

In light of the conducted study, a few critical observations emerged that underscore the efficacy and potential of the Novel ResNet-50 classifier compared to the KNN classifier. First and foremost, the precision in recognition: the Novel ResNet-50 classifier demonstrated an impressive accuracy of 97%, compared to the KNN's 94%. This clearly suggests the former's superiority in performance. A primary factor influencing this outcome is the deep architectural design of the ResNet-50, enabling it to effectively learn features from images across different scales.

Introducing six salient points to further illuminate this conclusion:

- Depth and Complexity: The depth of the ResNet-50 allows it to model complex patterns and relationships in the data, giving it an edge over more straightforward models like KNN.
- Adaptability: The ResNet-50's ability to adapt to varied image scales means it can process both macro and micro-level features, enhancing its detection capabilities.
- Computational Efficiency: Despite its depth, ResNet-50's skip connections ensure efficient training without the vanishing gradient problem, which often plagues deep networks.
- Generalization: The ResNet-50 model is less prone to overfitting, ensuring a good balance between bias and variance, leading to better generalisation on unseen data.
- Feature Extraction: The convolutional nature of the ResNet-50 allows it to excel in

extracting hierarchical features from images, a crucial aspect of image classification tasks.

• Versatility: Beyond the scope of this study, the ResNet-50's architecture is versatile and can be fine-tuned or adapted to various other tasks, showcasing its broad applicability.

In sum, while both classifiers have their merits, the comprehensive capabilities of the Novel ResNet-50 make it a formidable tool for tasks involving intricate image analysis. Its unique design, adaptability, and efficiency render it a particularly effective choice for discerning and capturing the nuanced features of visual data.

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