 ISSN 2502-3357 (online) | ISSN 2503-0477 (print)

Contents lists available at www.journal.unipdu.ac.id

Register

Journal Page is available to www.journal.unipdu.ac.id/index.php/register

Research article

Drowsy Eyes and Face Mask Detection for Car Drivers using the Embedded System

Rizqi Putri Nourma Budiarti [a,*], *Bagoes Wahyu Nugroho* [b], *Nisa Ayunda* [c], *Sritrusta Sukaridhoto* [d]

[a,b] *Department of Information Systems, Universitas Nahdlatul Ulama Surabaya, Jl. Jemursari 51-57, 60237, Surabaya, Indonesia*
[c] *Department of Mathematics, Universitas Pesantren Tinggi Darul Ulum, Kompleks PP. Darul Ulum Peterongan, 61481, Jombang, Indonesia*
[d] *Department of Creative Multimedia Technology, Politeknik Elektronika Negeri Surabaya, Jl. Raya ITS – Kampus PENS Sukolilo, 60111, Surabaya, Indonesia.*
email: [a*] rizqi.putri.nb@unusa.ac.id, [b] bagoeswahyu001.if17@student.unusa.ac.id, [b] nisaayunda@mipa.unipdu.ac.id, [b] dhoto@pens.ac.id
* Correspondence

ARTICLE INFO

Article history:
Received 15 November 2022
Revised 20 March 2023
Accepted 11 July 2023
Available online 20 July 2023

Keywords:
MobileNetV2;
Embedded System;
Support Vector Machine;
HOG;
Face Mask;

Please cite this article in IEEE style as:
R. P. N. Budiarti, B. W. Nugroho, N. Ayunda, and S. Sukaridhoto, "Drowsy Eyes and Face Mask Detection for Car Drivers using the Embedded System," *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 9, no. 1, pp. 86-94, 2023.

ABSTRACT

Efforts to prevent the spread of the COVID-19 virus have underscored the critical importance of mask-wearing as a preventive measure. Concurrently, road traffic accidents, often resulting from human error, have emerged as a significant contributor to global mortality rates. This study endeavors to address these pressing issues by employing advanced Deep Learning techniques to detect mask usage and identify drowsy eyes, thus contributing to the prevention of COVID-19 and accidents due to driver fatigue. To achieve this objective, an embedded system was developed, utilizing the integration of hardware and software components. The system effectively utilizes MobileNetV2 for face mask detection and employs HOG and SVM algorithms for drowsy eye detection. By seamlessly integrating these detection systems into a single embedded device, the simultaneous detection of both mask usage and drowsy eyes is made possible. The results demonstrates a commendable accuracy rate of 80% for face mask detection and 75% for drowsy eye detection. Furthermore, the mask detection component exhibits a remarkable training accuracy of 99%, while the drowsy eye detection component demonstrates an 80% training accuracy, affirming the system's efficacy in precisely identifying masks and drowsy eyes. The proposed embedded system offers potential applications in enhancing road safety. Its capability to effectively detect drowsy eyes and mask usage in car drivers contributes significantly to preventing accidents due to driver fatigue. Additionally, it plays a vital role in mitigating COVID-19 transmission by promoting widespread mask-wearing among individuals. This study exemplifies the potential of integrating Deep Learning methodologies with embedded systems, thus paving the way for future research and development in the realm of driver safety and virus prevention.

1. Introduction

The COVID-19 pandemic, which has impacted many countries around the world, began in December 2019. It is characterized by symptoms such as fever, cough, shortness of breath, body aches, and loss of sense of taste and smell. In severe cases, it can lead to death. The virus spreads through the air when an infected person sneezes or communicates with others. It can also spread through water droplets, commonly known as respiratory droplets, which are expelled from the mouth or nose of an infected person and disperse in the air.

Road traffic accidents are the leading cause of death worldwide [1]. In 2015, the Police recorded an average of 80 deaths per day, which translates to approximately 3 deaths per hour, due to traffic

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

accidents in Indonesia. Additional data from the World Health Organization (WHO) reveals that nearly 3,400 people died daily on global roads in 2016. The statistics concerning accidents involving motorized vehicles in Indonesia are alarmingly high. This can be observed from the accident rate data released by the KNKT (National Transportation Safety Committee) from 2010 to 2016, which recorded 41 accident investigations resulting in 443 deaths. One significant cause of accidents is driver error, specifically human error. Approximately 69.7% of motor vehicle accidents are attributed to human error, while the remaining accidents are largely caused by inadequate facilities and infrastructure. A prevalent factor contributing to human error is driver drowsiness.

The detection of a drowsy driver involves analyzing the driver's physiological state, facial pattern changes, and behavior while driving [2][3][4][5]. The driver's sleep detection system has been extensively researched, focusing on the application of image signal processing. Several methods can be employed, utilizing biological parameters and vehicle conditions [6]. Intensive studies related to drowsiness detection in drivers have been conducted. For instance, Szidonia Lefkovits conducted research on the use of Gabor filters for driver's eye detection, accurately identifying sleepiness; however, it may not be applicable to drivers wearing glasses [7]. Additionally, Maninder Kahlon and Subramaniam Ganesan developed a sleep detection system using binary eye image data. The system identifies the state of the eye (open or closed) by employing grayscale-to-binary image transformation. However, the accuracy of the resulting detection is influenced by lighting conditions and the driver's position, rendering the threshold value non-adaptive.

The MobilenetV2 network architecture optimizes memory consumption and execution speed, making experimentation and parameter setting easier. It utilizes convolutional feature layers to detect multiple scales of various sizes and uses several maps' features to improve the prediction accuracy of each class object. In the first layer, the convolutional block conv 1x1 is employed to expand the number of channels in the data, and the expansion layer functions to ensure that the output has more channels than the input in the data. Following that, depth-wise convolution filters the features as the source of the ReLU6 section. In the third layer, the 1x1 conv layer is used to project data with a high number of dimensions into a tensor with a lower number of dimensions known as the bottleneck layer[8][9][10][11].

TensorFlow is a versatile framework designed to enable computational graphs to run on various platforms and hardware environments, prioritizing portability. The unique aspect of identical codes allows TensorFlow neural networks to be adaptable, whether in a cloud environment distributed across multiple machines or on a single laptop. This flexibility makes the framework suitable for serving predictions on dedicated servers or mobile platforms like iOS or Android. In the context of embedded devices such as Raspberry Pi and NVIDIA: Jetson, TensorFlow can be utilized for prediction tasks. Specifically, NVIDIA: Jetson is a preferred embedded device for serving predictions. TensorFlow is compatible with multiple operating systems, including Windows, Linux, and MacOS[12][13][14][15].

The research study conducted by Nagrath et al. [16] focuses on a dataset labeled "with_mask" and "without_mask," which is categorized into two classes. The primary objective of the study was to predict whether someone is wearing a mask correctly. To achieve this, the authors employed two algorithms. In the first step, the images undergo preprocessing and are trained across the dataset. In the second step, the model trained in the previous phase is used to accurately detect face masks. The developed system serves as a reference for future applications and research. The system also serves as a reference for the following research applications, in which a real-time drowsiness eye detection feature is added [16][17][18][19].

In the study conducted by Abbas [20], a Hybrid Fatigue detection system was developed. This system incorporates both visual and non-visual features obtained from multiple cameras and ECG sensors. The initial stage of the system involves detecting the driver's face in the video footage. Subsequently, the system calculates the eye aspect ratio (EAR) and mouth aspect ratio (MAR) values to determine whether the driver's eyes are open or closed and whether yawning is occurring. Additionally, the system utilizes an ECG sensor to measure the driver's heart rate (bpm). The developed system serves as a reference for future research applications. Furthermore, a real-time mask detection feature is planned to be integrated into the system[2][6][10][20][21]. Related studies on the use of HOG and SVM algorithms for drowsy eye detection in drivers with different applications include: the use of HOG and

http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

SVM features to enhance driver safety and security [22][23], the use of HOG and SVM features to prevent traffic accidents[24], and the use of HOG and SVM features to improve detection accuracy[25].

2. Materials and Methods

The methodology employed in this research comprises multiple stages aimed at developing an efficient and reliable system. The primary objective of this research is to create a solution capable of detecting whether a car driver is drowsy or wearing a mask, utilizing embedded system technology.

Figure 1 illustrates the block diagram of the research approach to monitor drowsy eyes and face masks. The system uses a driver's camera, with a webcam strategically positioned to capture the driver's frontal facial image [26]. Subsequently, the frames are extracted to obtain 2-dimensional images[27]. The MobileNetV2 model is utilized to detect the face mask within the frames, while the HOG and SVM algorithm are employed to detect drowsy eyes (Eye Detection) within the frame.

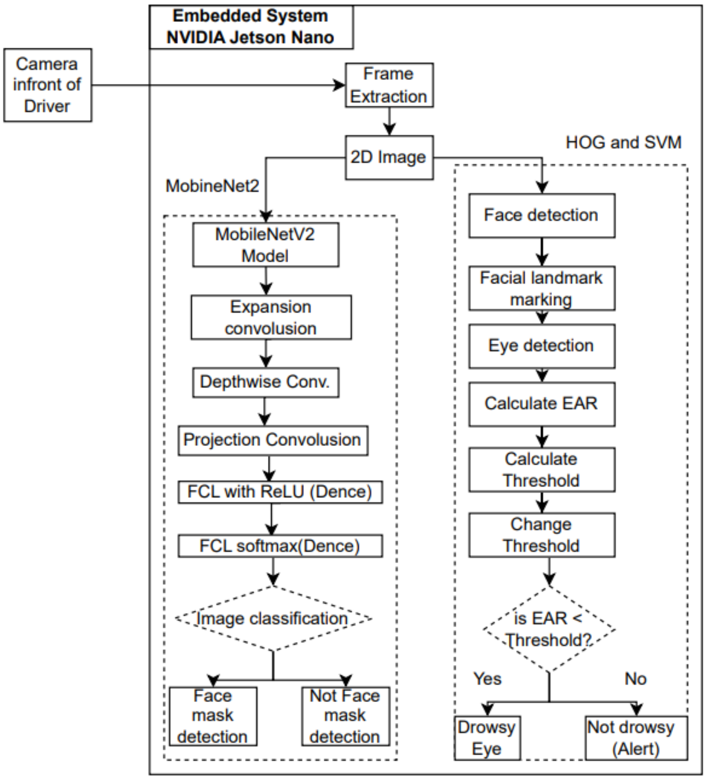


Fig. 1. The block diagram of the research

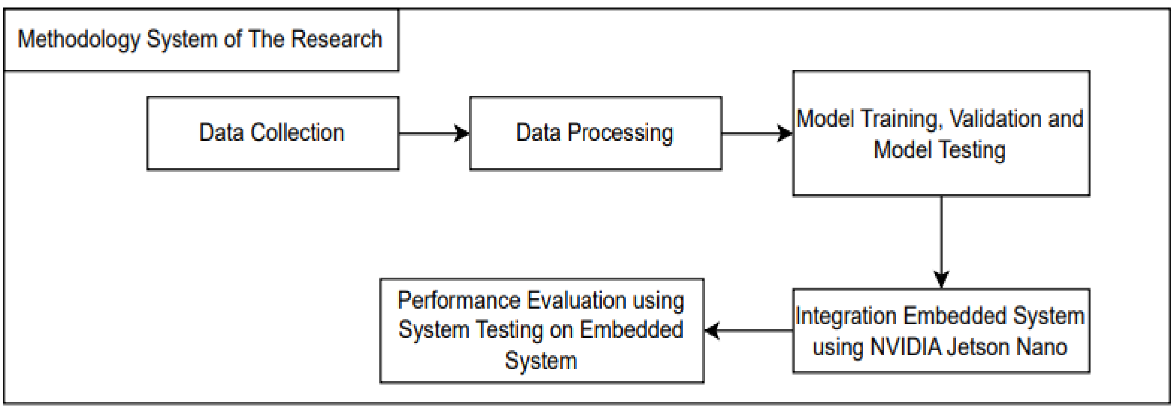


Fig. 2. Methodology system of the research

2.1. Data Collection

The initial stage of this research is dedicated to data collection. The primary dataset was sourced from Kaggle's dataset, comprising 1387 open-eyed images and 1320 closed images, totaling 2707 images. Furthermore, images of individuals both wearing and not wearing masks were included, resulting in a total of 1500 images each, and thus making the overall dataset consist of 3000 images. These images

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

were then divided into training data and testing data, creating a collection of training and testing images.

2.2. Data Processing

2.2.1 Resizing images (for mask detection) and facial landmark histogram (for drowsy eyes detection)

After collecting the dataset, the mask detection process continued with data pre-processing. Initially, the data was cleaned to remove, identified, and correct damaged or poor-quality images. Subsequently, the images were converted into a dataset for input. The next step involved resizing or equalizing the size of all image dimensions to 224 pixels. The images were sorted alphanumerically, converted into a tensor, and then transformed into an array format. Finally, the image was scaled within the range of [-1,1].

In the drowsy eye detection section, a face detector is utilized, which is a combination of Histogram of Oriented Gradients (HOG) features, linear classification, pyramid image, and other techniques, implemented using the software library called dlib. The process starts by dividing the image into a grid of interconnected small networks and calculating the gradient. Then, a histogram is derived from this gradient, and these histograms are combined.

2.3. Model Training, Validation and Model Testing

The dataset is typically divided into three subsets: training, validation, and testing sets. The training set is used to train the model, the validation set is used to tune hyperparameters and evaluate the model's performance during training, and the testing set is used to assess the final performance of the trained model. MobileNetV2, which consists of depth-wise separable convolutions and inverted residual blocks, was employed as a feature extractor for various computer vision tasks. The model was trained using the training set by iterating over the data for a specified number of epochs. After that, different experiments were conducted with varying values, and the model's performance on the validation set was evaluated to find the best combination. Once the training process was complete, the final model's performance was evaluated using the testing set.

2.4. Integration with Embedded System using NVIDIA Jetson Nano

All previous processes were then applied to existing embedded devices such as NVIDIA Jetson, which functions like a small computer to process the previously mentioned method, equipped with a camera as a detection tool. The NVIDIA Jetson Nano is a powerful embedded computing platform specifically designed for AI and computer vision applications [28][29][30]. It includes the TensorFlow framework, which is a software framework for numerical computing based on data flow graphs. TensorFlow serves as an interface for providing and implementing machine learning algorithms, primarily deep learning networks. Some applications utilize object detection from the TensorFlow library, and previously, developers had to create a dataset and train models on their own computer [31].

2.5. Performance Evaluation using System Testing on the Embedded System

After successfully applying the model to the embedded device, the system testing process was carried out to visualize the detection results. When the driver's face is detected, the system displays a box containing percentage information and detection details for mask detection. For drowsiness detection, a green mark is displayed around the detected eye area. If the eye area shows signs of narrowing or reaches the threshold limit of 0.25 within a time length of 45 frames, the system triggers a notification indicating the drowsiness status.

3. Results and Discussion

In this section, we evaluate the methodologies employed by various algorithms utilized in this research. These methodologies include the examination of hardware devices used, the results of face mask detection tests, drowsy eye detection tests, and the evaluation of an embedded system in a car, as well as the outcomes obtained from testing each detection system. Within this research, we conducted a thorough investigation of the current methodologies employed in the field and critically assess the algorithms and techniques used for face mask detection and drowsy eye detection. Additionally, we explored the hardware devices used in the experiments, such as cameras or sensors, along with the specific configurations and settings implemented. The study details the process of conducting tests to evaluate the performance and effectiveness of the detection systems. For face mask detection tests, the research presents the collected data and analyzes the accuracy, precision, and recall of the detection

 http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

system. We thoroughly evaluate the system's ability to correctly identify and classify individuals wearing face masks during the testing process. Comprehensive insights into the challenges and limitations encountered during the testing process are provided. The research also discusses the accuracy, precision, and recall of the face mask detection system and the system's capability to correctly identify individuals wearing face masks.

Similarly, drowsy eye detection tests are conducted meticulously. The research explains the experimental setup, which includes the use of eye-tracking devices or video recordings to monitor eye behavior. We then analyze the obtained results and discuss the accuracy, sensitivity, and specificity of the drowsy eye detection system. Additionally, the research evaluates the embedded system's integration into a car environment, examining its practical implementation and performance in real-time contexts. Detailed insights are provided regarding the results obtained from the face mask detection tests, drowsy eye detection tests, and the evaluation of the embedded system in a car. The analysis of the results is supported by statistical measures and comparisons to validate the effectiveness and reliability of the detection systems. The results of the tests in this research cover the hardware devices used, the face mask detection test results, the drowsy eye detection test results, and the evaluation of the embedded system in a car. Each detection system's performance is thoroughly discussed and analyzed in this section.

3.1. Hardware specifications

The deep learning and evaluation process is carried out on the NVIDIA Jetson Nano device, while the dataset creation process and training are performed on a laptop. The specifications of both the NVIDIA Jetson Nano and the laptop used for training are shown in the following table:

Table 1. Hardware Specifications

No	Description	Spesification
1	**NVIDIA Jetson Nano**	
	- CPU	Quad-core ARM® Cortex®-A57 @ 1.43 GHz
	- GPU	NVIDIA Maxwell™ with 128 NVIDIA CUDA® cores
	- Memory	4 GB 64-bit LPDDR4 1600MHz - 25.6 GB/s
	- Storage	64 GB
	- OS	NVIDIA Linux4Tegra (L4T) 32.1
2	**Laptop**	
	- CPU	Intel(R) Core(TM) i7-1065G7 @ 1.3GHz
	- GPU	NVIDIA GeForce GTX 1650 Max-Q Design 4GB
	- Memory	16 GB
	- Storage	500 GB
	- OS	Windows 10

3.2. Face Mask Detection Test

In this section, we utilize the MobileNetV2 algorithm for face mask detection. This algorithm utilizes convolutional neural network (CNN) architecture, which is specifically designed for object detection on mobile devices with limited resources and combines concepts from various techniques, including depthwise separable convolutions and bottleneck layers. The key features of MobileNetV2 include Depthwise Separable Convolution, Bottleneck Layer, Inverted Residuals with Linear Bottlenecks, and Network Structure.

The first key feature, depthwise separable convolution, separates the convolution operation into two stages: depthwise convolution, which convolves each input channel separately, and pointwise convolution, which combines the channels. This significantly reduces the number of parameters without sacrificing detection quality. Meanwhile, the bottleneck layer used to reduce the number of channels in the feature map before performing convolutional operations. This helps reduce computational complexity while preserving important information representation.

On the feature inverted residuals with linear bottlenecks, MobileNetV2 utilizes inverted residual blocks with linear bottlenecks as its basic units. Each block consists of a 1x1 convolution to reduce the number of channels, followed by depthwise separable convolution, and ends with another 1x1 convolution to restore the channel count. Beside that, on the feature network structure, MobileNetV2 has a deep network structure, comprising multiple blocks with different resolution scales. In the early

http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

layers, higher resolution scales are used to obtain better spatial information, while lower resolution scales are employed in deeper layers to extract more abstract features.

Each selected model was trained with epochs for feature extraction, and we uses steps per epoch and re-compile the model. After the training process was complete, a mask detection test was performed on images from the camera. Human faces that are detected will be surrounded by a green border box, while faces not wearing masks will have a red border box. In Figure 2, the results of testing mask detection on the Embedded System Jetson Nano are shown. The findings indicate that out of the 20 analyzed facial images, 16 human faces were accurately recognized, resulting in a mask detection accuracy rate of 80%.

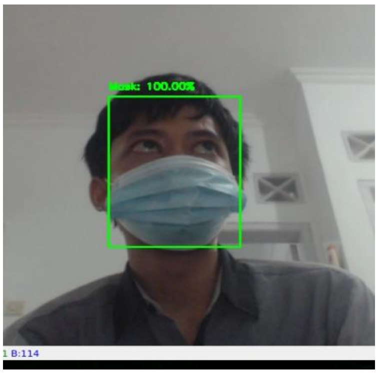


Fig. 3. The result of face mask detection

3.3. Drowsy Eye Detection Test

In this section, we utilized two algorithms: HOG (Histogram of Oriented Gradients) and SVM (Support Vector Machine) for drowsy eye detection. The HOG method calculates the distribution of gradient orientations within local image regions, quantifying the shape and texture information by dividing the image into small cells and computing histograms of gradient orientations within each cell. These histograms capture the local structure and provide discriminative information for drowsy eye detection. After extracting the HOG features, we train an SVM model to learn the patterns associated with drowsy eyes and normal states. SVM is a supervised learning algorithm that uses a decision boundary to separate different classes in the feature space. In sleep detection, the SVM model is trained on labeled drowsy eye and normal (open eyes) data to find an optimal hyperplane that maximally separates the two classes. The dataset is preprocessed, and the extracted features are used to train the SVM classifier with the labeled dataset.

Subsequently, drowsy eye detection tests were carried out on images from the camera. Using the two algorithms, we provided marks on the results. Specifically, the detected eye will be marked with a green border box around the eye area. If the eye area shows an increasingly narrowed area or reaches the threshold limit of 0.25 for a length of time equal to 45 frames, a notification of sleepiness status will be triggered. In Figure 3, the results of testing drowsy eye detection on the Embedded System Jetson Nano are shown. The findings indicate that out of the 20 analyzed facial images, 15 human facial conditions were accurately identified, resulting in a drowsy eye detection accuracy rate of 75%.

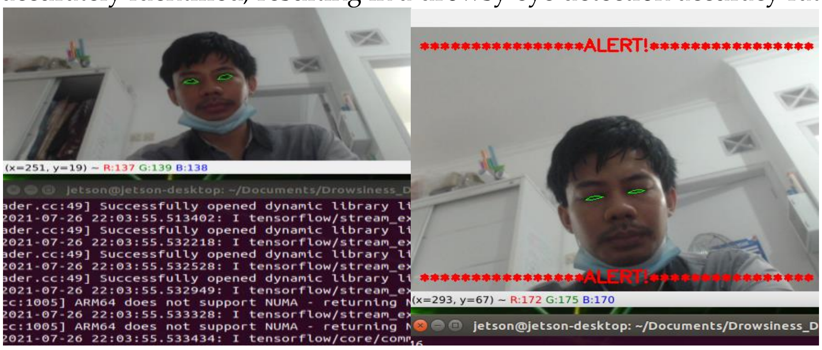


Fig. 4. The result of drowsy eye detection

3.4. Drowsy Eye Detection Test

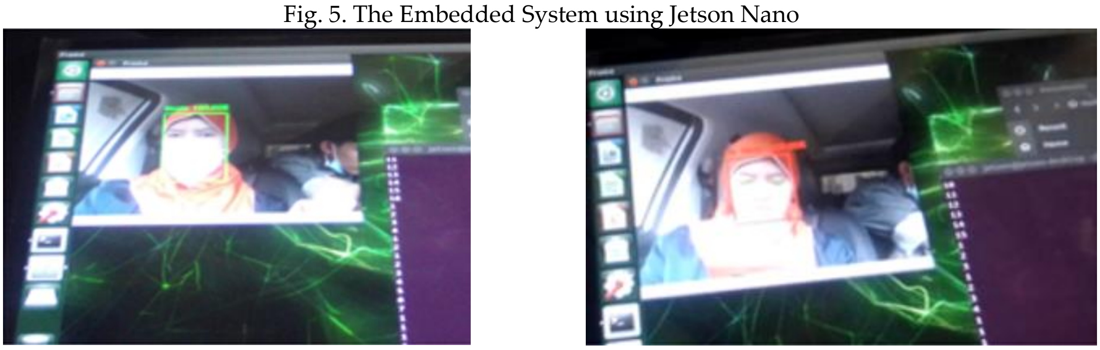
In this section, the system that has been prepared with the required embedded system using Jetson Nano is tested. The purpose of this test was to check if the embedded system and the detection program

http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

can be loaded and work properly in a car. The test results show that the embedded system performs well, successfully detecting the use of face masks and drowsy eyes. The IoT setting is depicted in Figure 4, and the results of the running system are shown in Figure 5.

Fig. 5. The Embedded System using Jetson Nano



(a) (b)

Fig. 6. Embedded system test results in the car (a) Face mask detection (b) Drowsy eye with an alert to the driver.

In this phase, a series of tests were conducted, which included generating training reports, Receiver Operating Characteristics (ROC) graphs, and computing the Area Under the Curve (AUC) values. These tests involved using the trained model and varying the number of epochs during the experimentation process. Detailed training reports were generated during the tests to assess the model's performance. These reports provided valuable insights into various metrics, such as accuracy, loss, and convergence. By analyzing these metrics, the researchers gained a comprehensive understanding of the model's behavior and performance trends throughout the training process.

Receiver Operating Characteristics (ROC) graphs were also constructed to evaluate the ability of the model to differentiate between different classes. These graphs visually depict the trade-off between true positive rates and false positive rates at various classification thresholds. By examining the ROC curves, we can assess the model's sensitivity and specificity and determine the optimal threshold for classification. In these experiments, we varied the number of epochs, which represents the number of times the entire training dataset was passed through the model during training. By adjusting this parameter, we explored the impact of different training durations on the model's performance. This allowed us to analyze how the model's accuracy, convergence, and other metrics evolved as the training progressed.

Table 5. Accuracy and AUC results

Detail	Epoch	100	200	300	400	500	600
FaceMask Detection	Accuracy	99%	99%	99%	99%	99%	99%
	AUC	0,99	0,99	0,99	0,99	0,99	0,99
Drowsy Eye Detection	Accuracy	80%	80%	83%	84%	84%	84%
	AUC	0,79	0,80	0,82	0,83	0,83	0,83

The results obtained during the testing phase, where we varied the number of epochs for both face mask and drowsy eye detection, are presented in Table 5. The findings clearly demonstrate that the face mask detection system achieved an impressive accuracy of approximately 99%, outperforming the drowsy eye detection system, which showed a commendable accuracy rate of around 83%.

4. Conclusions

Based on the conducted tests and thorough analyses, we can draw the following conclusions: The mask detection system, integrated into an embedded system, exhibits a commendable accuracy rate of 80% in detecting faces of individuals wearing masks. Similarly, the eye detection system on the embedded system achieves an accuracy rate of 75% in detecting the faces of the same individuals. The deep

http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

learning-based Mask and Drowsy Eyes Detection system, which incorporates glasses recognition, showcases promising accuracy in detecting faces, eyes, and identifying the presence of glasses.

To further advance this research, several limitations were identified. Addressing these shortcomings may involve enriching the dataset with a larger and more diverse set of conditions. Additionally, incorporating cameras with higher resolution capabilities could significantly enhance the detection performance. These improvements hold the potential to achieve more precise and reliable results in face and eye detection.

Regarding future applications, the research presents promising potential for deployment in various contexts, including travel cars and online ride-sharing services like GrabCar or GoCar. By incorporating the Mask and Drowsy Eyes Detection system into vehicles, it can play a vital role in enhancing safety measures and providing timely alerts to drivers concerning potential risks associated with mask usage and drowsiness. These findings underscore the effectiveness and versatility of the developed deep learning-based detection system. Further advancements in dataset quality, camera technology, and real-world integration hold the promise of achieving even greater accuracy and reliability in detection capabilities in the future.

References

[1] WHO, "Global Status Report on Road Safety," World Health Organization, Geneva, 2018. [Online]. Available: https://www.who.int/publications-detail/global-statusreport-on-road-safety-2018

[2] Y.-Y. Lin and P.-A. Hsiung, “An early warning system for predicting driver fatigue,” in *2017 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW)*, 2017, pp. 283–284.

[3] C. Huda, H. Tolle, and F. Utaminingrum, “Mobile-based driver sleepiness detection using facial landmarks and analysis of EAR values,” 2020.

[4] S. D. Lin, J.-J. Lin, and C.-Y. Chung, “Sleepy eye’s recognition for drowsiness detection,” in *2013 International Symposium on Biometrics and Security Technologies*, 2013, pp. 176–179.

[5] R. Jabbar, M. Shinoy, M. Kharbeche, K. Al-Khalifa, M. Krichen, and K. Barkaoui, “Driver drowsiness detection model using convolutional neural networks techniques for android application,” in *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)*, 2020, pp. 237–242.

[6] I. Gupta, N. Garg, A. Aggarwal, N. Nepalia, and B. Verma, “Real-time driver’s drowsiness monitoring based on dynamically varying threshold,” in *2018 Eleventh International Conference on Contemporary Computing (IC3)*, 2018, pp. 1–6.

[7] S. Lefkovits, L. Lefkovits, and S. Emerich, “Detecting the eye and its openness with Gabor filters,” in *2017 5th International Symposium on Digital Forensic and Security (ISDFS)*, 2017, pp. 1–5.

[8] W. Rahmaniar and A. Hernawan, “Real-time human detection using deep learning on embedded platforms: A review,” *J. Robot. Control*, vol. 2, no. 6, pp. 462–468, 2021.

[9] P. Liu, H. Chi, X. Li, and D. Li, “Development of a fatigue detection and early warning system for crane operators: A preliminary study,” in *Construction Research Congress 2020*, 2020, pp. 106–115.

[10] M. F. Shakeel, N. A. Bajwa, A. M. Anwaar, A. Sohail, and A. Khan, “Detecting driver drowsiness in real time through deep learning based object detection,” in *International work-conference on artificial neural networks*, 2019, pp. 283–296.

[11] J. Cao, R. Pang, R. Ma, and Y. Qi, “Face Mask Recognition Based on MTCNN and MobileNet,” in *Advances in Simulation and Process Modelling: Proceedings of the Second International Symposium on Simulation and Process Modelling (ISSPM 2020) 2*, 2021, pp. 433–442.

[12] T. Hope, Y. S. Resheff, and I. Lieder, *Learning tensorflow: A guide to building deep learning systems*. “ O’Reilly Media, Inc.,” 2017.

[13] Y. S. Taspinar and M. Selek, “Object recognition with hybrid deep learning methods and testing on embedded systems,” *Int. J. Intell. Syst. Appl. Eng.*, vol. 8, no. 2, pp. 71–77, 2020.

[14] S. U. Rehman, M. R. Razzaq, and M. H. Hussian, “Training of SSD (single shot detector) for facial detection using Nvidia jetson nano,” *arXiv Prepr. arXiv2105.13906*, 2021.

 http://doi.org/10.26594/register.v9i1.2612

ISSN 2502-3357 (online) | ISSN 2503-0477 (print)
9 (1) January 2023 86-94

[15] J. Tang, D. Sun, S. Liu, and J.-L. Gaudiot, "Enabling deep learning on IoT devices," *Computer (Long. Beach. Calif).*, vol. 50, no. 10, pp. 92–96, 2017.

[16] P. Nagrath, R. Jain, A. Madan, R. Arora, P. Kataria, and J. Hemanth, "SSDMNV2: A real time DNN-based face mask detection system using single shot multibox detector and MobileNetV2," *Sustain. cities Soc.*, vol. 66, p. 102692, 2021.

[17] G. Jignesh Chowdary, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, "Face mask detection using transfer learning of inceptionv3," in *Big Data Analytics: 8th International Conference, BDA 2020, Sonepat, India, December 15--18, 2020, Proceedings 8*, 2020, pp. 81–90.

[18] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, "A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic," *Measurement*, vol. 167, p. 108288, 2021.

[19] M. Jiang and X. Fan, "Retinamask: A face mask detector," 2020.

[20] Q. Abbas, "HybridFatigue: A real-time driver drowsiness detection using hybrid features and transfer learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 1, 2020.

[21] M. Kahlon and S. Ganesan, "Driver drowsiness detection system based on binary eyes image data," in *2018 IEEE International Conference on Electro/Information Technology (EIT)*, 2018, pp. 209–215.

[22] V. Pavani, M. N. Swetha, Y. Prasanthi, K. Kavya, and M. Pavithra, "Drowsy Driver Monitoring Using Machine Learning and Visible Actions," in *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, 2022, pp. 1269–1279.

[23] R. R. Varghese, P. M. Jacob, J. Jacob, M. N. Babu, R. Ravikanth, and S. M. George, "An Integrated Framework for Driver Drowsiness Detection and Alcohol Intoxication using Machine Learning," in *2021 International Conference on Data Analytics for Business and Industry (ICDABI)*, 2021, pp. 531–536.

[24] A. Al Redhaei, Y. Albadawi, S. Mohamed, and A. Alnoman, "Realtime Driver Drowsiness Detection Using Machine Learning," in *2022 Advances in Science and Engineering Technology International Conferences (ASET)*, 2022, pp. 1–6.

[25] A. Celecia, K. Figueiredo, M. Vellasco, and R. González, "A portable fuzzy driver drowsiness estimation system," *Sensors*, vol. 20, no. 15, p. 4093, 2020.

[26] S. Menon, J. Swathi, S. K. Anit, A. P. Nair, and S. Sarath, "Driver face recognition and sober drunk classification using thermal images," in *2019 International Conference on Communication and Signal Processing (ICCSP)*, 2019, pp. 400–404.

[27] H. Kaufman, J. Woods, S. Dravida, and A. Tekalp, "Estimation and identification of two-dimensional images," *IEEE Trans. Automat. Contr.*, vol. 28, no. 7, pp. 745–756, 1983.

[28] S. Cass, "Nvidia makes it easy to embed AI: The Jetson nano packs a lot of machine-learning power into DIY projects-[Hands on]," *IEEE Spectr.*, vol. 57, no. 7, pp. 14–16, 2020.

[29] A. A. Süzen, B. Duman, and B. \cSen, "Benchmark analysis of jetson tx2, jetson nano and raspberry pi using deep-cnn," in *2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, 2020, pp. 1–5.

[30] V. Sati, S. M. Sánchez, N. Shoeibi, A. Arora, and J. M. Corchado, "Face detection and recognition, face emotion recognition through NVIDIA Jetson Nano," in *Ambient Intelligence--Software and Applications: 11th International Symposium on Ambient Intelligence*, 2021, pp. 177–185.

[31] S. Sukaridhoto, D. K. Basuki, H. Yulianus, and R. P. N. Budiarti, "Performance Evaluation of Integrated Deep Learning Web Platform for Dataset Training," *Appl. Technol. Comput. Sci. J.*, vol. 2, no. 2, pp. 117–128, 2019.

 http://doi.org/10.26594/register.v9i1.2612