ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 3, December 2024

MODEL GHT-SVM FOR TRAFFIC SIGN DETECTION USING SUPPORT VECTOR MACHINE ALGORITHM BASED ON GABOR FILTER AND TOP-BLACK HAT TRANSFORM

Handrie Noprisson[1], Vina Ayumi[2], Erwin Dwika Putra[3], Marissa Utami[4], Nur Ani[5]

[1,2] Department of Informatics, Faculty of Engineering and Informatics, Universitas Dian Nusantara
[3,4]Computer Vision Research Laboratory, PT Towwar Tech Ind3
[5]Institute of Visual Informatics, Universiti Kebangsaan Malaysia

email: vina.ayumi@dosen.undira.ac.id [1], handrie.noprisson@dosen.undira.ac.id[2], edp@towwarind.tech[3]
utami@towwarind.tech[4], p93828@siswa.ukm.edu.my[5]

Abstract

A factor that can hinder the traffic sign recognition of is the variation in lighting in the image of signs. This study aims to detect traffic symbols using Gabor Filter (GFT), Top Hat Transform (THT), and Black Hat Transform (BHT) methods on the Support Vector Machine (SVM) algorithm for traffic sign dataset images with data problems that tend to have dark backgrounds at night and bright backgrounds during the day. From the experimental results, GHT-SVM gets the highest accuracy compared to HSV-SVM, HSV-RF, HSV-KNN, and H2T-SVM models. Based on experimental results, H2T-SVM from HOG ⊕ THT ⊕ BHT ⊕ SVM results get the best accuracy of 86.42%. The Gabor Filter (GFT) parameters used are the number of filters with a value of 16, k-size with a value of 30, sigma with a standard deviation value of 3.0, lambd with a sinusoidal factor value of 10.0, gamma with a spatial aspect ratio value of 0.5 and psi with a phase offset value of 0 while the Top Hat Transform (THT) and Black Hat Transform (BHT) methods use filterSize sizes with values (3,3).

Keywords : Black Hat Transform, Top Hat Transform, Gabor Filter, Support Vector Machine, Traffic Signs

Received: 04-04-2024 | **Revised:** 06-06-2024 | **Accepted:** 04-10-2024
DOI: https://doi.org/10.23887/janapati.v13i3.75778

INTRODUCTION

Recognition of traffic sign automatically is is urgently needed for developing smart driver systems. The sign of traffic symbol have several distinctive features that can be used for symbol identification [1]. These symbols are formulated in unambiguous forms and colors, with symbol or script in sign contrasting strongly with the background. The form of traffic symbols, such as shapes and colors, can be used as a distinguishing feature of traffic symbols so that they can be classified into specific groups [2], [3].

The computerized traffic symbol identification is critical to help regulate traffic and guide drivers and pedestrians by providing important information and warnings [4]. In addition, automatic automatic traffic sign detection is important to prevent accidents and vehicle damage by warning drivers about traffic signs and preventing them from breaking the law [5], [6]. This detection model can be developed for autonomous vehicles and intelligent transportation systems, allowing them to recognize and understand traffic signs in real time. With a machine learning approach, traffic signs can be detected and recognized simultaneously as warnings in smart car designs. Automatic traffic sign detection can prevent accidents and facilitate the development of advanced and autonomous driver assistance systems [7]–[11].

The computerized traffic symbol identification is a study aimed at developing warning systems for driving safety [12], [13]. Several research studies have focused on this area using machine learning techniques. One approach is the implementation of a Support Vector Machine (SVM, for short). Madhuri & and Madhavi (2023) developed a traffic symbol identification system that combines color and shape information for traffic sign classification [8]. Sugiharto et al. (2022) offered a traffic symbol detection model by utilizing HSV color segmentation and SVM classification, accomplishing an accuracy of 79.05%. The same model was also used by other studies, achieving 79.64% accuracy with Random Forest and 81.65% with K-Nearest Neighbors (KNN) [14].

However, in the data collected traffic sign dataset images tend to have a dark background at night and a background too bright during the day [9], [15], [16]. To overcome this, there needs to be optimization of top or black hat transform method. The top-hat transform technique is used to improve the quality of unknown objects on a dark background and retrieve missing information in the image. In addition, the black-hat transform technique is used to enhance bright objects on a light background and is often used for feature extraction. These two transformation techniques play an essential responsibility in the task of processing traffic sign images and impact to improving the quality and accuracy of detection results [17]–[24].

In addition, this study will use the Gabor Filter method to improve the color of the collected imagery. The Gabor Filter method is used for color rendering of images, where Gabor filters are used to preprocess images and preserve detailed features while avoiding loss of information. Another reason Gabor Filter is texture classification, where it is used to capture visual content and extract texture features that are invariant to rotation and scaling [25]–[27].

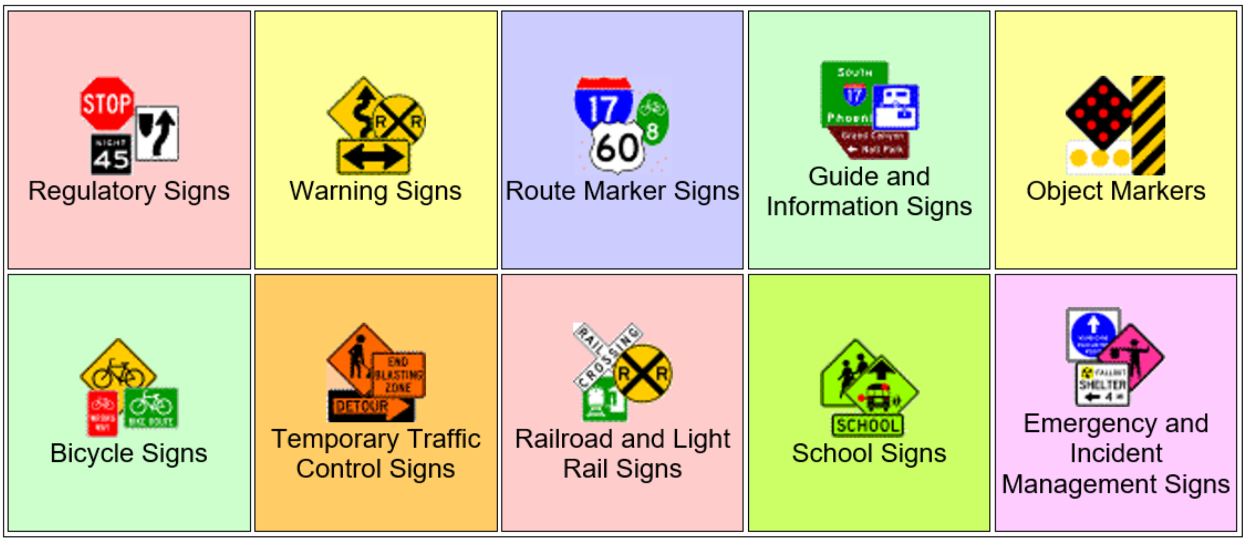
Based on the background above, this study uses a Support Vector Machine (SVM) and is optimized with Top Hat and Black Hat Transform and classify traffic sign dataset images with data problems that tend to have dark backgrounds at night and bright backgrounds during the day.

METHOD

This research aims to use the top hat and black hat transform method on machine learning algorithms to detect traffic symbols. The dataset used uses the dataset used in the previous study [28]–[30]. The data used in this study amounted to 6358 data. This study focuses on "Route Marker Signs" and "Guide and Information Signs" which are divided into 10 classes namely "GuideSign", "M1", "M4, "M5", "M6", "M7", "P1", "P10_50", "P12", "W1" as seen in Figure 1.

The stages used in this study are based on the implementation of a SVM and optimized with Top Hat Transform (THT) and Black Hat Transform (BHT) and see the role of feature extraction between HOG or Histogram of Oriented Gradients and Gabor Filter (GFT) in image classification of traffic sign datasets.

The conventional method of SVM does not support multiclass classification because it was only developed to support binary classification and separate data points into two classes. To support multiclass classifications such as image classification of traffic sign datasets, there needs to be a One-to-One implementation that breaks down multiclass problems into binary classification problems. This research consists of 6 stages of research by applying three feature extraction methods. The stages of research in detail can be seen in Figure 2.



References: [30]

Figure 1. Class of Research Dataset

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 3, December 2024

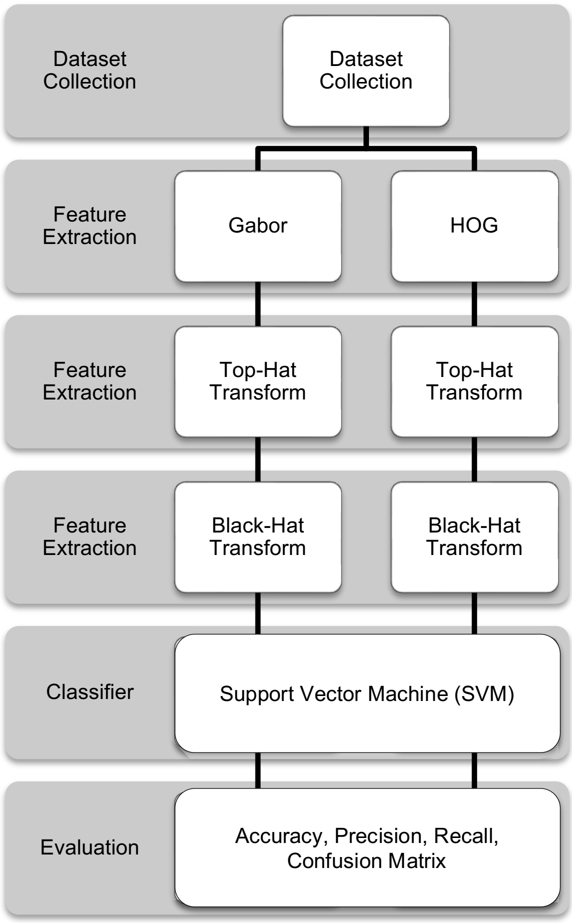


Figure 2. Research Phase

The dataset in this study was converted to image size into uniform dimensions. The dataset is allocated into symbol data for training and symbol data for testing. This experiment will be carried out by applying the top-black hat transform method to the support vector machine algorithm. The Gabor Filter parameters used are num_filters with value of 16, ksize with value of 30, sigma with value of 3.0, lambd with value of 10.0, gamma with value of 0.5, and psi with value of 0, while the top hat and black hat transform method use filterSize =(3, 3). This research contributes to developing advanced driver assistance systems, by examining feature extraction, training, and classification stages using Top Hat Transform (THT) and Black Hat Transform (BHT) methods on machine learning algorithms.

RESULT AND DISCUSSION

Machine learning can be used to classify traffic signs by utilizing various techniques and algorithms. One approach is to use the Support Vector Machine for object identification, such as recognizing and categorizing traffic signs.

Another approach is to use methods for image feature extraction and SVM for training and classification. In addition, SVM algorithms can be applied to classify objects with high accuracy even under adverse conditions. The SVM algorithm can also be used simultaneously with Top Hat Transform (THT) and Black Hat Transform (BHT) to classify traffic signs.

Teknik dengan menggunakan Top Hat Transform dan Bottom Hat Transform telah banyak digunakan dalam penelitian image processing, khususnya pada penelitian yang memiliki pencahayaan tidak teratur. Teknik Top Hat Transform ini mengombinasikan pengurangan citra grayscale dengan opening sedangkan teknik Bottom Hat Transform mengombinasikan pengurangan citra grayscale dengan closing

In this section, two main experiments will be described. The first experiment was an analysis using the GHT-SVM (GFT$\oplus$ THT $\oplus$ BHT model) which is a combination of Gabor Filter (GFT), Top Hat Transform (THT), and Black Hat Transform (BHT). The second experiment was an analysis using the H2T-SVM (HOG $\oplus$

THT ⊕ BHT model) which is a combination of Histogram Oriented Gradients (HOG), Top Hat Transform (THT), and Black Hat Transform (BHT).

The accomplishment of the recommended GHT-SVM and H2T-SVM models was evaluated using precision, recall, accuracy and f1-score models. Refers to the results of the performance evaluation, the GHT-SVM model obtained is precision of 87%, recall of 86%, f1-score with value of 86%, and accuracy with score of 86.42%. The results of accuracy score, precision score, recall score, and f1-score performance analysis from the GHT-SVM model can be seen in Table 1.

Table 1. Evaluation Score of GHT-SVM

Class	Precision	Recall	F1-score
Guide_Sign	0.84	0.87	0.86
M_1	0.53	0.71	0.61
M_4	0.94	0.89	0.92
M_5	0.67	0.67	0.67
M_6	0.60	0.60	0.46
M_7	0.80	0.80	0.87
P_1	0.81	0.81	0.87
P_10_50	1.00	1.00	1.00
P_12	1.00	1.00	1.00
W_1	1.00	1.00	0.77

The second experiment was an analysis using H2T-SVM (HOG ⊕ THT ⊕ BHT model) which is a combination of Histogram Oriented Gradients (HOG), Top Hat Transform (THT), and Black Hat Transform (BHT) getting a precision of 87%, recall of 86%, f1-score with value of 86%, and score of accuracy is 86.11%. The results of accuracy score, precision score, recall score, and f1-score performance analysis from the H2T-SVM model can be investigated in Table 2.

Table 2. Evaluation Score of H2T-SVM

Class	Precision	Recall	F1-score
Guide_Sign	0.80	0.82	0.81
M_1	0.61	0.79	0.69
M_4	0.92	0.91	0.92
M_5	0.67	0.67	0.67
M_6	1.00	0.38	0.55
M_7	0.81	0.88	0.85
P_1	0.80	0.86	0.83
P_10_50	1.00	1.00	1.00
P_12	1.00	1.00	1.00
W_1	1.00	0.75	0.86

Paramater of HOG in this experiment is conducted using orientations with value 9, pixels_per_cell with value (8, 8) , cells_per_block with value (2, 2), block_norm with value 'L2-Hys', visualize with value True, and transform_sqrt with value True. Another evaluation model used is the confusion matrix. This evaluation model is useful for explaining the performance matrix of the H2T-SVM classification model in correctly or incorrectly predicting the class of data. The results of the confusion matrix analysis from the H2T-SVM model can be investigated in Figure 3.

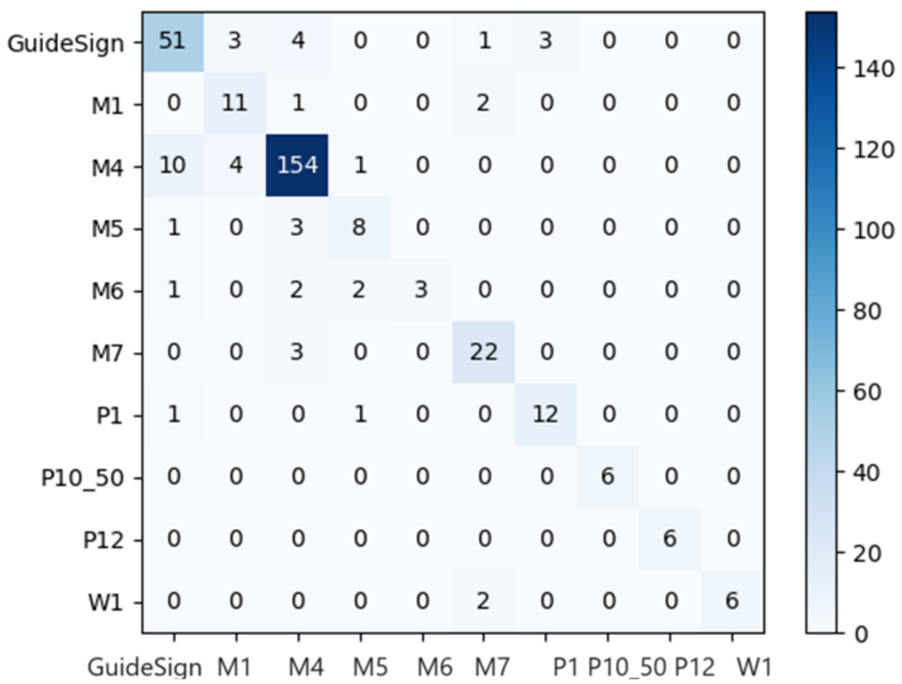


Figure 3. Confusion Matrix of H2T-SVM

The confusion matrix calculates the prediction results of the GHT-SVM model with the original class from the data and then calculates the number of true or false predictions from the GHT-SVM model in each class category. There are four variables used in the confusion matrix variables, namely true positive (TP, for short), false positive (FP), false negative (FN, for short), and true negative or TN. The results of the confusion matrix analysis from the GHT-SVM model can be investigated in Figure 4.

The GHT-SVM approach involves pre-processing, feature extraction, training, and classification stages, and SVM can be implemented with Top Hat Transform (THT) and Black Hat Transform (BHT). The GHT-SVM model uses a Gabor Filter (GFT) with a num-filters parameter value of 16, ksize parameter value of 30, sigma parameter value of 3.0, lambd with parameter value of 10.0, gamma parameter value of 0.5, and psi parameter value of 0 and Top Hat Transform (THT) and Black Hat Transform (BHT) methods with filterSize parameter parameter value of (3,3). The comparison of the accuracy value of GHT-SVM can be seen in Figure 5 and Table 3.

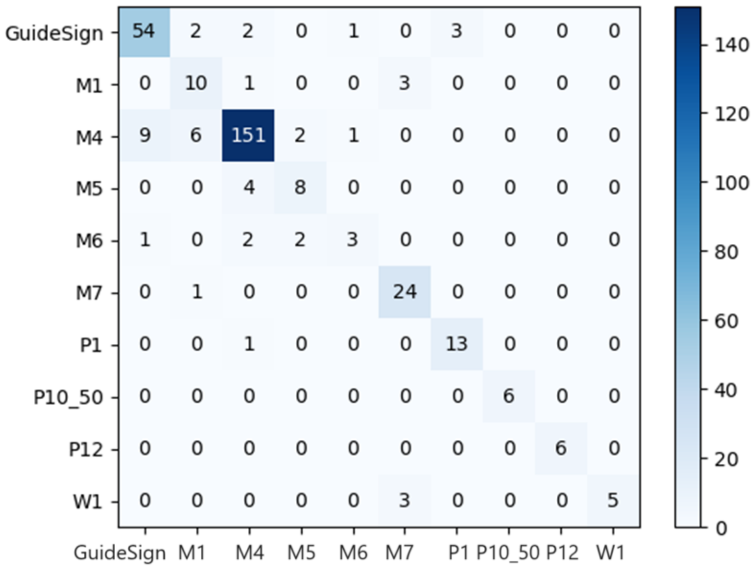


Figure 4. Confusion matrix of GHT-SVM

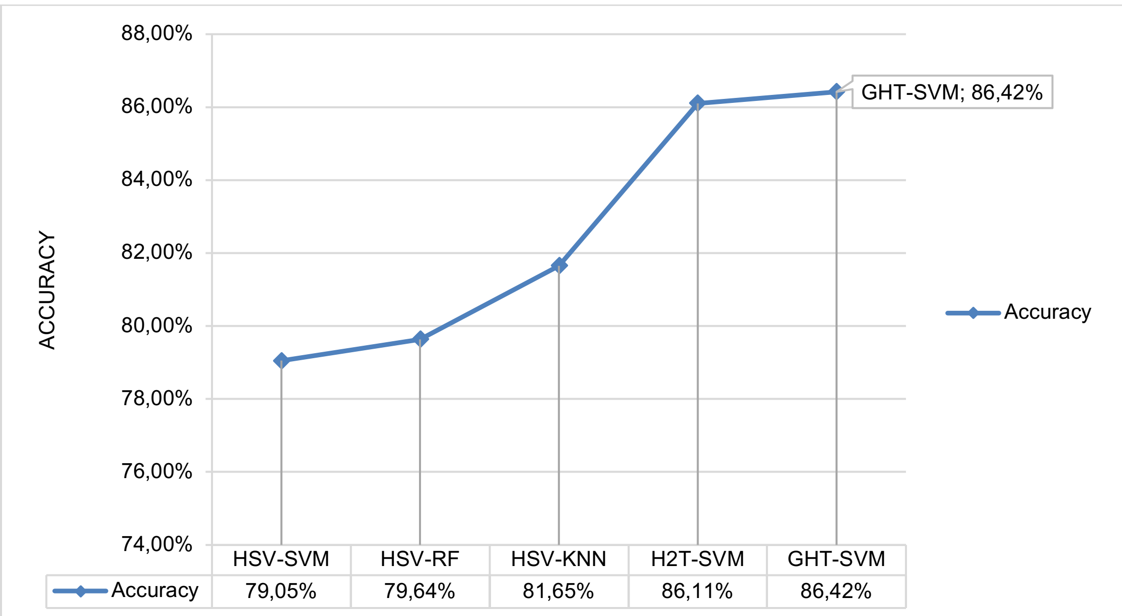


Figure 5. GHT-SVM Performance

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 3, December 2024

Table 3. Comparison of Research Model

Model	Feature Extraction	Classifier	Accuracy (%)	Reference
HSV-SVM	HSV	SVM	79,05	[14]
HSV-RF	HSV	RF	79,64	[14]
HSV-KNN	HSV	KNN	81,65	[14]
H2T-SVM	HOG ⊕ THT ⊕ BHT	SVM	86,11	Proposed Model
GHT-SVM	GFT⊕ THT ⊕ BHT	SVM	86,42	Proposed Model

Based on the results of the study, the GHT-SVM model has the best performance. The GHT-SVM model is a combination of GFT⊕ THT ⊕ BHT and SVM. The advantage of the GFT method is that it is able to identify images very well in extracting the characteristics of an object. In traffic sign identification, the GFT method is able to work very well by eliminating image variability parameters that often interfere with the process of recognition, identification, or classification of an image.

The GFT method is a linear filter used in extracting traffic sign features as a feature detector. From the experimental results, the GFT method as a characteristic detector is successful because it has the ability to eliminate variabilities caused by contrast illumination and slight image shift and deformation. The results of applying the GFT method to traffic light images can be investigated in Figure 6.

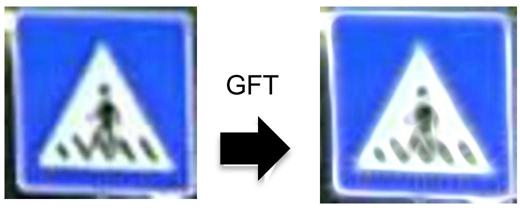


Figure 6. Image of GFT Implementation

Before being processed using THT ⊕ BHT, the traffic sign image is processed by converting it to grayscale. The next process is carried out by the opening morphology and closing morphology processes to produce a good image in the THT ⊕ BHT process. The grayscale value reduction in the THT method uses the opening morphology process while the BHT method uses the grayscale image in the closing morphology process to reduce the value.

Morphology is a digital image processing technique using shape as a guideline in processing. The value of each pixel in the resulting digital image is obtained through a comparison process between the corresponding pixels in the input digital image with neighboring pixels. The operation of morphology depends on the order in which the pixels appear so that morphological techniques are suitable when used to process binary and grayscale images.

Techniques using THT ⊕ BHT have been widely used in image processing research, especially in research that has irregular lighting. This THT technique combines grayscale image reduction with opening while BHT technique combines grayscale image reduction with closing. The results of applying the THT ⊕ BHT method to traffic light images can be investigated in Figure 7.

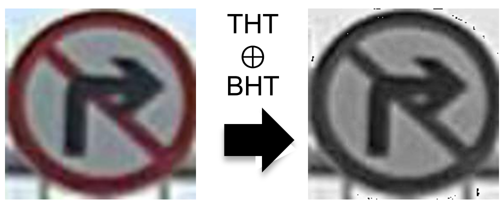


Figure 7. Image of THT ⊕ BHT Implementation

This research used GFT⊕ THT ⊕ BHT in preprocessing phase. The role GFT method is to covert linear filter used in extracting traffic sign features as a feature detector. Then THT ⊕ BHT is to sharp the object of traffic sign object. The results of applying the GFT⊕ THT ⊕ BHT method to traffic light images can be seen in Figure 8.

After implementation, GFT⊕ THT ⊕ BHT on traffic signs, then the input in image form will be treated using the SVM algorithm. The SVM method has several types of kernels, namely kernels with linear form, kernels with polynomial form, radial basic function or RBF kernels and kernel with sigmoid form. The kernel used in this study is a 'linear' kernel. Selection of kernel implementations based on Figure 9.

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
Volume 13, Issue 3, December 2024

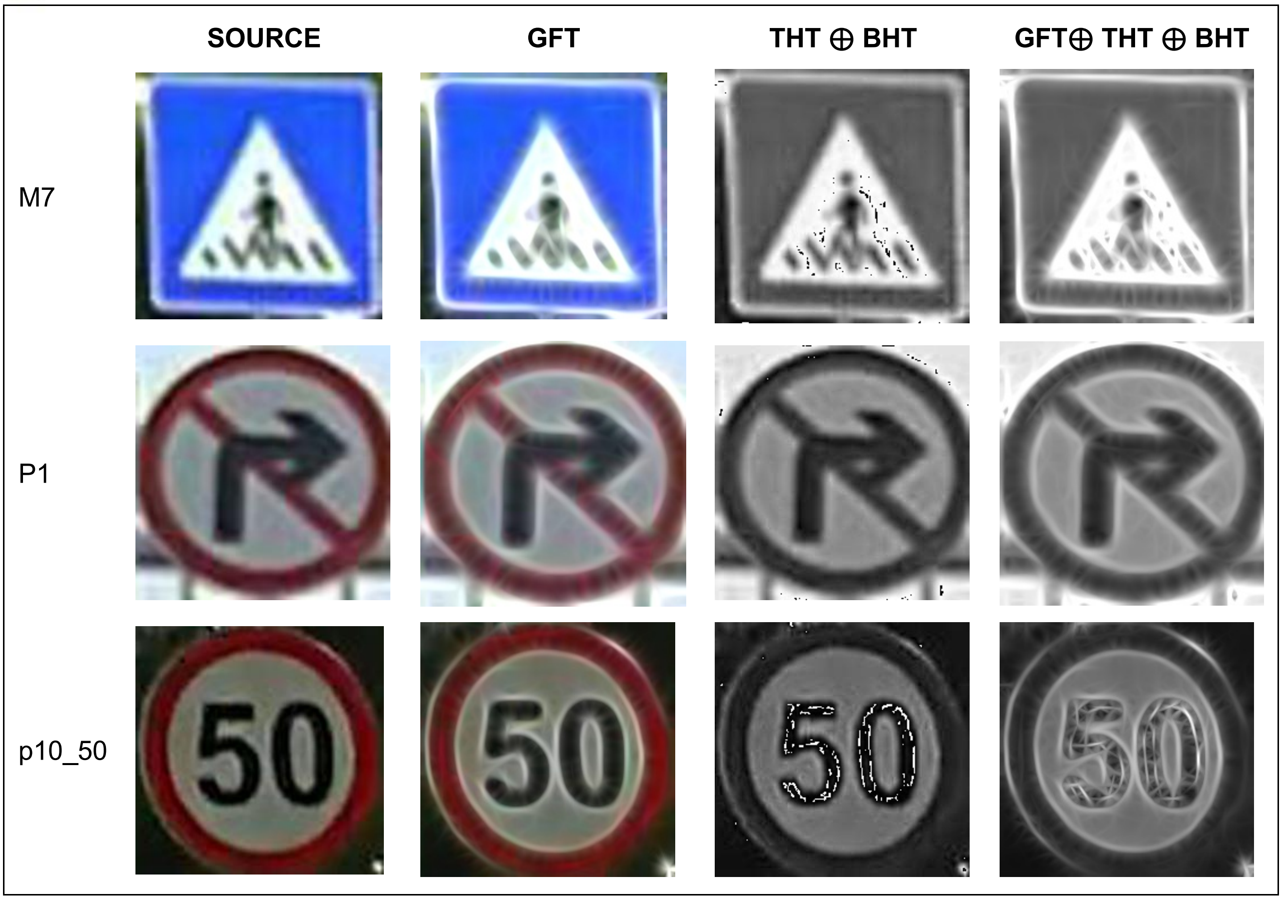


Figure 8. Image of GFT⊕ THT ⊕ BHT Implementation

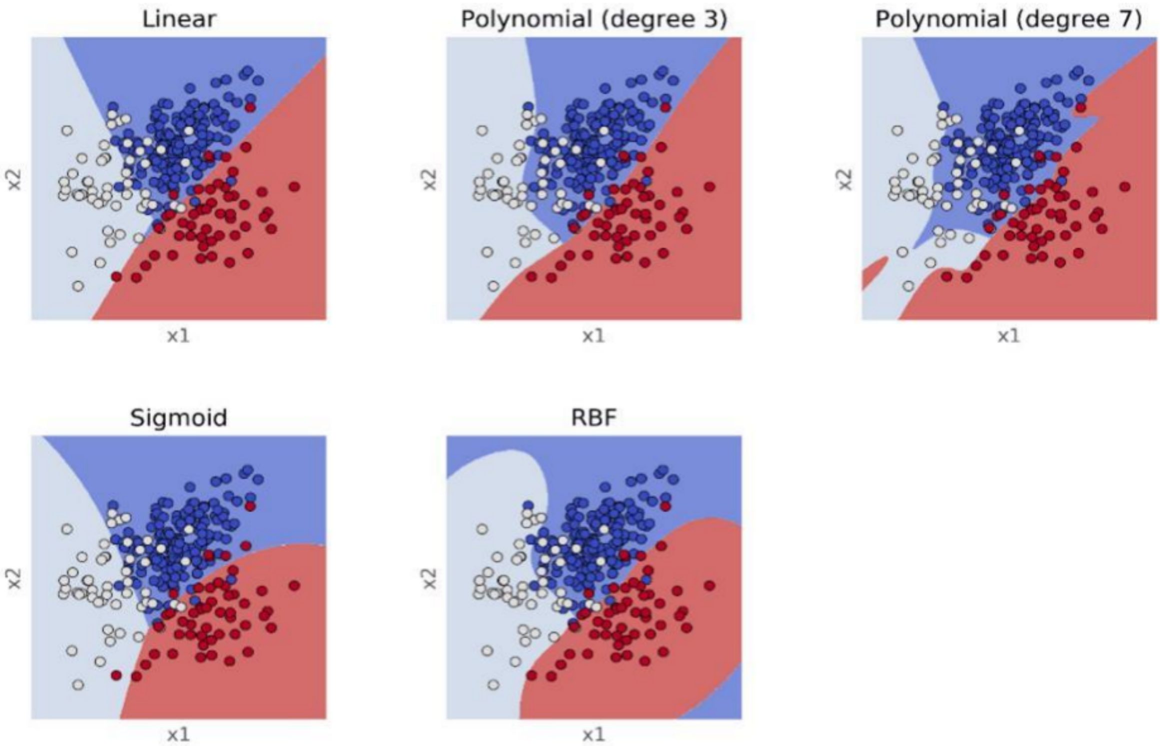


Figure 9. Illustration of SVM kernel [31]

CONCLUSION

Some factors that can hinder effective traffic sign detection and recognition include variations in perspective, lighting variations, and damage to traffic signs. This research will classify traffic symbols with various classes by applying Gabor Filter (GFT), Top Hat Transform (THT), and Black Hat Transform (BHT) methods to the Support Vector Machine (SVM) algorithm. Based on experimental results, H2T-SVM from HOG ⊕ THT ⊕ BHT ⊕ SVM results get the best accuracy of 86.42%. The Gabor Filter (GFT) parameters used are the number of filters with a value of 16, ksize with a value of 30, sigma with a standard deviation value of 3.0, lambd with a sinusoidal factor value of 10.0, gamma with a spatial aspect ratio value of 0.5 and psi with a phase offset value of 0 while the Top Hat Transform (THT) and Black Hat Transform (BHT) methods use filterSize sizes with values (3, 3).

The suggestion for future research is feature extraction analysis on color feature extraction combined with texture feature extraction that has been carried out in this study. In addition, dataset quality can be improved with contrast enhancement, and the amount of data can be expanded using augmentation data so that the data is more diverse and the model obtains better performance. Then, the issue of multi-class imbalanced data classification for M4 class will be solved by using LogitBoost algorithms in future research.

ACKNOWLEDGMENT

The research of smart traffic sign identification is supported by LRPM Universitas Dian Nusantara by providing the research facilities and funds.

REFERENCES

[1] J. Chen, K. Jia, W. Chen, Z. Lv, and R. Zhang, “A real-time and high-precision method for small traffic-signs recognition,” *Neural Comput. Appl.*, vol. 34, no. 3, pp. 2233–2245, 2022.

[2] P. Kornpitack and S. Sawmong, “Empirical analysis of factors influencing student satisfaction with online learning systems during the COVID-19 pandemic in Thailand,” *Heliyon*, vol. 8, no. 3, 2022.

[3] X. Bangquan and W. X. Xiong, “Real-time embedded traffic sign recognition using efficient convolutional neural network,” *IEEE Access*, vol. 7, pp. 53330–53346, 2019.

[4] N. Triki, M. Karray, and M. Ksantini, “A real-time traffic sign recognition method using a new attention-based deep convolutional neural network for smart vehicles,” *Appl. Sci.*, vol. 13, no. 8, p. 4793, 2023.

[5] V. Truelove, M. Nicolls, K. B. Stefanidis, and O. Oviedo-Trespalacios, “Road rule enforcement and where to find it: An investigation of applications used to avoid detection when violating traffic rules,” *J. Safety Res.*, vol. 87, pp. 431–445, 2023.

[6] J. Wishart *et al.*, “Driving safety performance assessment metrics for ads-equipped vehicles,” *SAE Int. J. Adv. Curr. Pract. Mobil.*, vol. 2, no. 2020-01–1206, pp. 2881–2899, 2020.

[7] C. M. Rao, M. S. S. Jahnavi, V. S. Madhuri, M. Disha, and V. S. Rao, “Traffic Sign Recognition for Automated Vehicles using ML Algorithm,” in *2023 7th International Conference on Trends in Electronics and Informatics (ICOEI)*, 2023, pp. 1232–1237.

[8] P. Madhuri and G. B. Madhavi, “Automatic Traffic Sign Detection and Classification,” *Int. J. Sci. Technol. Eng.*, vol. 11, no. 6, pp. 3685–3690, 2023.

[9] C. Dewi, R.-C. Chen, Y.-T. Liu, and S.-K. Tai, “Synthetic Data generation using DCGAN for improved traffic sign recognition,” *Neural Comput. Appl.*, vol. 34, no. 24, pp. 21465–21480, 2022.

[10] R. Zhang, A. Ishikawa, W. Wang, B. Striner, and O. K. Tonguz, “Using reinforcement learning with partial vehicle detection for intelligent traffic signal control,” *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 1, pp. 404–415, 2020.

[11] W. A. Haque, S. Arefin, A. S. M. Shihavuddin, and M. A. Hasan, “DeepThin: A novel lightweight CNN architecture for traffic sign recognition without GPU requirements,” *Expert Syst. Appl.*, vol. 168, p. 114481, 2021.

[12] A. Zaibi, A. Ladgham, and A. Sakly, “A lightweight model for traffic sign classification based on enhanced LeNet-5 network,” *J. Sensors*, vol. 2021, pp. 1–13, 2021.

[13] I. Singh, S. K. Singh, S. Kumar, and K. Aggarwal, “Dropout-VGG based convolutional neural network for traffic sign categorization,” in *Congress on Intelligent Systems: Proceedings of CIS 2021, Volume 1*, 2022, pp. 247–261.

[14] A. Sugiharto *et al.*, “Comparison of SVM, Random Forest and KNN Classification By Using HOG on Traffic Sign Detection,” in *2022 6th International Conference on Informatics and Computational Sciences (ICICoS)*, 2022, pp. 60–65.

[15] D. Temel, G. Kwon, M. Prabhushankar, and G. AlRegib, "CURE-TSR: Challenging unreal and real environments for traffic sign recognition," *arXiv Prepr. arXiv1712.02463*, 2017.
[16] Y. Hua, "An efficient traffic classification scheme using embedded feature selection and lightgbm," in *2020 Information Communication Technologies Conference (ICTC)*, 2020, pp. 125–130.
[17] N. Aishwarya, M. Muthulakshmi, and B. S. Abirami, "Contrast Enhanced Multi-Modal Image Fusion using Top hat transform and Sparse Dictionary," in *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, 2022, pp. 01–07.
[18] I. G. N. A. D. Saputra, I. G. A. M. Sunaya, I. B. Sugirianta, and I. G. N. B. C. Bawa, "Combination of Top-Hat and Bottom-Hat Transforms for Frequency Estimation," in *2018 International Conference on Applied Science and Technology (iCAST)*, 2018, pp. 687–692.
[19] Y. Liu, J. Peng, J.-H. Xue, Y. Chen, and Z.-H. Fu, "TSingNet: Scale-aware and context-rich feature learning for traffic sign detection and recognition in the wild," *Neurocomputing*, vol. 447, pp. 10–22, 2021.
[20] Y. Zhu and W. Q. Yan, "Traffic sign recognition based on deep learning," *Multimed. Tools Appl.*, vol. 81, no. 13, pp. 17779–17791, 2022.
[21] C. Dewi, R.-C. Chen, X. Jiang, and H. Yu, "Deep convolutional neural network for enhancing traffic sign recognition developed on Yolo V4," *Multimed. Tools Appl.*, vol. 81, no. 26, pp. 37821–37845, 2022.
[22] K. Zhou, Y. Zhan, and D. Fu, "Learning region-based attention network for traffic sign recognition," *Sensors*, vol. 21, no. 3, p. 686, 2021.
[23] C. Lin, L. Li, W. Luo, K. C. P. Wang, and J. Guo, "Transfer learning based traffic sign recognition using inception-v3 model," *Period. Polytech. Transp. Eng.*, vol. 47, no. 3, pp. 242–250, 2019.
[24] C. Dewi, R.-C. Chen, and H. Yu, "Weight analysis for various prohibitory sign detection and recognition using deep learning," *Multimed. Tools Appl.*, vol. 79, no. 43–44, pp. 32897–32915, 2020.
[25] H. Li, M. Zhang, Z. Yu, Z. Li, and N. Li, "An improved pix2pix model based on Gabor filter for robust color image rendering," *Math. Biosci. Eng.*, vol. 19, no. 1, pp. 86–101, 2022.
[26] A. W. Muzaffar *et al.*, "Gabor Contrast Patterns: A Novel Framework to Extract Features From Texture Images," *IEEE Access*, vol. 11, pp. 60324–60334, 2023.
[27] W. Tang, F. Jia, and X. Wang, "Image Large Rotation and Scale Estimation Using the Gabor Filter," *Electronics*, vol. 11, no. 21, p. 3471, Oct. 2022.
[28] T. Surinwarangkoon, S. Nitsuwat, and E. Moore, "A traffic sign detection and recognition system," *Int. J. Circuits, Syst. Signal Process.*, vol. 7, no. 1, pp. 58–65, 2013.
[29] J. Wang, "Traffic Sign Classification and Recognition," *Institute of Software Chinese Academy of Sciences*, 2022. [Online]. Available: https://www.kaggle.com/datasets/wjybuqi/traffic-sign-classification-and-recognition.
[30] R. C. Moeur, "Manual Traffic Sign," *Moeurgineering*, 2019. [Online]. Available: http://www.trafficsign.us/.
[31] R. Zhang, Z. Lin, S. Chen, Z. Lin, and X. Liang, "Multi-factor stock selection model based on kernel support vector machine," *J. Math. Res*, vol. 10, no. 9, 2018.