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RESEARCH ARTICLE

Real-Time Classification of Vehicles Using Machine Learning Algorithm on the Extensive Dataset

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ABSTRACT Vehicle classification (VC) is a prominent research domain within image processing and machine learning (ML) for identifying vehicle volumes and traffic rule violations. In developed countries, nearly 40% of daily accidents are fatal, while in developing countries, the figure rises to 70%. Traditionally, vehicle detection and classification have been performed manually by experts, which is difficult, time-consuming, and prone to errors. Furthermore, incorrect detection and classification can result in hazardous situations. This highlights the need for more reliable techniques to identify and classify vehicles accurately and practically. In existing applications, numerous automated methods have been proposed. However, employing deep and machine learning algorithms on complex datasets of vehicle images has failed to achieve accuracy in various climate conditions and has been time-consuming. This paper presents an accurate, robust, real-time system to classify vehicles from onsite roads. The proposed system utilizes a random wavelet transform for pre-processing, edge and region-based segmentation for feature extraction, an embedded method for feature selection, and the XGBoost algorithm for VC. The proposed work classifies vehicles under complex weather, illumination, color, and occlusion conditions over 10 datasets, including a novel dataset named SRM2KTR, containing 75,436 vehicle images on an FPGA platform. The results show 98.81% accuracy, outperforming the state-of-the-art (98%). The system was demonstrated with four different classifiers, classifying images in 0.16 ns with an average accuracy of 97.79%. The system exhibits high accuracy, rapid identification time, and robustness in practical use.

INDEX TERMS Vehicle classification, machine learning, eXtreme gradient boost algorithm.

I. INTRODUCTION

Intelligent transportation systems (ITS) have a profound impact on the classification of vehicles through video surveillance, contributing to vehicle tracking, accident prevention, and route identification [1], [2]. Transportation bottlenecks lead to environmental pollution and increased user travel time, which can have economic repercussions. Therefore, integrating vehicle information into information technology and communication (ICT) is essential for real-time traffic monitoring, improved mobility, and congestion reduction. In this context, ITS plays a crucial role in vehicle identification through computer vision and its application in machine learning. To achieve accurate vehicle classification despite challenges such as varying illumination, shadows, and occlusions, an algorithm is employed. Diverse vehicles in terms of structure, color, and model are used to train the classification model [3], [4]. To represent specific vehicle characteristics, a high-performing ensemble machine learning algorithm, XGBoost, is utilized. Accurate estimation of

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traffic-related factors necessitates the tracking and analysis of vehicle parameters.

The computer-based approach for unique model identification of vehicles hinges on a two-step process involving feature selection and vehicle classification. Initially, vehicle features are extracted and then subjected to a selection process. Subsequently, these selected features are employed to train a classifier, enabling it to categorize vehicles effectively. In light of these considerations, extensive research has been conducted, yielding a range of feature selection methods and ensemble classifiers. Notably, the selected features encompass both global attributes (e.g., class, shape, model) and local descriptors (such as BRISK, MSER, FREAK) [5], [6]. Classifier algorithms leverage sophisticated mathematical and statistical techniques to categorize vehicles based on the input data's likelihood [7], [8]. Among these algorithms, XGBoost stands out as one of the most widely utilized classifiers for vehicle image classification. Several experts in the field have demonstrated XGBoost's superior performance in specific applications, even when prior task-specific knowledge is not mandatory. For example, the co-occurrence matrix has proven highly effective in medical image analysis but less so in other domains. Similarly, character descriptors excel in text recognition but may be less efficient in different tasks. In the realm of object and vehicle detection, learning descriptors have demonstrated their capability to yield superior results. Furthermore, vehicle classification relies on correlating predefined pattern classes or machine learning-based pretrained vehicle images with various locations to identify vehicles within a specific area, even with varying positions, which presents a more hypothetical scenario.

Commonly, the inclusion of non-vehicle classes is employed to enhance overall classification performance. In scenarios involving predefined patterns, this approach can be time-consuming due to the necessity of correlating test images with multiple classes. Conversely, in machine learning (ML), utilizing pre-trained vehicle images stands out as a more efficient method for current vehicle classification, offering advantages in processing speed and accuracy [9], [10]. Presently, research primarily addresses low or moderately scaled datasets for vehicle classification, such as VEDAI, DLR-3K, and DOTA. These datasets, although valuable, have limitations in constructing highly complex and state-of-the-art statistical models for vehicle categorization, chiefly due to their limited vehicle class diversity and representation. Consequently, incorporating larger-scale datasets becomes imperative for advancing the field of normal vehicle image classification and recognition. The introduction of additional large-scale vehicle datasets is essential for developing advanced vehicle representation learning algorithms, which can also cater to different aspects of vehicle images, including vehicle re-identification and multiclass generation. As a result, a novel large-scale benchmark dataset, SRM2KTR, has been created. SRM2KTR comprises nearly 1,038,115 images, including 75,436 images across 10 categories related to various vehicle classes, such as two-wheelers, four-wheelers, LMVs (Light Motor Vehicles), and HMVs (Heavy Motor Vehicles).

In stark contrast to the existing VEDAI vehicle datasets, the newly proposed dataset surpasses them in both the number of classes and the volume of images, thus demonstrating superior dimensions and scalability. To achieve a high standard of images, meticulous processes such as dimension modeling, data refinement, elimination of redundancies, and multiple expert reviews have been diligently executed. This large-scale (LS) dataset holds immense value for advancing the field of vehicle image representation learning, particularly in the context of vision-based vehicle classification. Furthermore, the SRM2KTR dataset anticipates a new paradigm for large-scale visual vehicle detection, contributing significantly to the advancement of vehicle classification. Building upon these datasets, the paper introduces techniques like random and wavelet transforms for pre-processing, feature extraction involving edge and region-based segmentation, and an embedded feature selection method, all aimed at enhancing the effectiveness of vehicle classification.

An advanced training strategy has been implemented to systematically capture a wide array of vehicle features from vehicle images, encompassing a diverse range of model data. This approach involves the comprehensive examination of both global and fine-grained data during the training process. Simultaneously, the proposed prototype or model effectively incorporates various scales of local descriptors, enhancing local feature representation and, thus, the model's adaptability. A thorough evaluation of the SRM2KTR dataset underscores the effectiveness of the proposed XGBoost techniques. Furthermore, extensive experiments have been conducted, examining various state-of-the-art techniques for vehicle image representation learning, emerging models, fine-grained processes, and prevalent vehicle classification (VC) methods. Ensemble learning on large-scale datasets holds promise for addressing diverse vehicle-related computer vision tasks, including vehicle detection and classification, vehicle image retrieval, cross-modal vehicle retrieval, vehicle identification, and segmentation. These advancements signify improved generalization capacity. Implementing this state-of-the-art algorithm on the provided dataset is expected to offer substantial assistance across a broad spectrum of offline tasks centered around vehicles, especially those of a complex and developmental nature.

The contribution of our paper can be summarized as follows:

- The novel LS top-quality SRM2KTR dataset is provided with 1,038,115 images containing 10 categories.
- The random and wavelet transform is used for pre-processing technique, in which images are augmented and compressed.
- The edge and region-based segmentation are used for the feature extraction process, in which the data are extracted and dimensions are reduced.

- The embedded method for feature selection aims to increase the efficiency of the classifier model.
- The XGBoost algorithm is used in the classifier model for the efficient classification of vehicles.
- Different models are trained on SRM2KTR to convert into various vehicle-relevant tasks including visual vehicle recognition, retrieval, detection, segmentation, and cross-modal categories retrieval, and to determine its better generalization of SRM2KTR on these tasks.

The structure of this paper is organized as follows: Section II provides a comprehensive review of related work focusing on vehicle classification with machine learning algorithms. In Section III, the paper delves into an explanation of XGBoost. Section IV outlines the FPGA implementation of vehicle classification using the XGBoost Algorithm. The experimental setup for FPGA implementation with XGBoost is detailed in Section V. Lastly, the concluding section offers a summary of the paper's findings and insights.

II. RELATED WORK AND PROBLEM DESCRIPTION

This section conducts a review of the most relevant research on vehicle classification across large-scale (LS) datasets employing classifier techniques. In recent years, vehicle classification (VC) methods have been a focal point of research within the realm of image processing, incorporating machine learning techniques involving coils, sensors, videos, and more. With the burgeoning global population and increasing vehicular demand, the development of intelligent traffic monitoring systems has become imperative to manage city traffic effectively. Nevertheless, these techniques encounter formidable challenges, including climatic variations, low luminance conditions, varying camera positions, and noise interference. VC predominantly revolves around feature extraction and classification. Initially, features are extracted to train the classifier, and the classification model is subsequently employed to categorize the vehicles. In this context, [1] presents a robust YOLOv4-based vehicle identification model that effectively deciphers the distinguishing features within images. A feature pyramid network is integrated to enhance the efficacy of features for VC. This approach achieves a mean average precision (mAP) of 83.45% and 77.08% on BIT-Vehicle and UA-DETRAC vehicle datasets, respectively, each consisting of approximately 10,000 vehicle images across multiple classes. Additionally, diverse modes of data fusion are explored for extracting valuable information, which finds applications in various use cases. In the domain of vehicle detection and tracking, precision is notably improved, especially in non-line-of-sight environments. The study in [2] demonstrates performance enhancements, achieving 9.39% in Area Under the Curve (AUC) and 7.66% in Average Precision (AP) across three different datasets. Worth noting is the absence of annotated images in this context.

To address this limitation, [3] investigates the acquisition of information from unannotated images, encompassing data such as bounding boxes, images, and point-level labeling. Additionally, semantic segmentation is leveraged to differentiate between the internal and external vehicle components. The experiments conducted on the BSB vehicle dataset involve the manipulation of over 120,000 unique vehicle polygons derived from 1,066 DL samples with spatial dimensions of 256 × 256. Notably, real-time vehicle detection in traffic areas is not within the scope of this study. Instead, the paper proposes an EnsembleNet model for traffic density estimation, achieving an accuracy rate of 98% and enabling vehicle identification using various types of images, fine-tuning the models [4]. Likewise, hybrid methodologies have been deployed in the realm of vehicle classification (VC). For instance, in [11], the author introduced a hybrid model that combines Faster RCNN and YOLO for vehicle and traffic flow detection within a traffic scene dataset. Additionally, the study explores the predominance of voting classifiers, comparing their performance with the base estimator across various vehicle datasets. The utilization of the Cityscapes dataset, comprising 8 categories and 30 subcategories with a total of 5,000 images, is pivotal in the context of vehicle detection. Due to its robust perception and decision-making capabilities, this dataset is highly sought after in applications related to autonomous driving, leveraging edge intelligence for enhanced data security and overall scalability. The proposed approach yields an accuracy of 86.22% and a mean Intersection over Union (mIOU) of 75.63%, although it does not address complex scenes. In a different vein, [12] presents brain-inspired technology for traffic management systems, employing the YOLOv3 model for vehicle detection and classification under complex scenarios. This innovative approach utilizes vehicle images from Kaggle and Google's platforms, incorporating 160 images spanning 5 different classes. The results indicate an impressive average precision of 94.1% and a recall rate of 86.3%.

Furthermore, the model incorporates the highly accurate, stable, and speedy Mobilenet network [13], [14], which offers both technical and non-technical support for the implementation of single-stage object detection, addressing the challenges associated with identifying small objects. The model's efficacy is demonstrated on the BDD100K and KITTI datasets, each comprising 7,481 images, achieving precision rates of 82.59% and 84.83%, respectively. In the realm of traffic information, encompassing parameters such as flow, speed, and vehicle types, novel approaches are adopted to bridge various learning methods with transformer technology, enhancing the accuracy of driving condition predictions. Notably, a Cars Overhead with Context dataset is introduced for experimentation, featuring vehicle detection in diverse weather conditions. The combination of densely connected convolutional networks and transformer in transformer layers results in accuracy improvements ranging from 5% to 10% when compared to PoolFormer and ViT [15], [16], [17]. Deep learning-based CSPDarknet53 is introduced as a means to minimize traffic congestion by identifying vehicles from the DAWN dataset, achieving a mean average precision of 86% [18], [19]. Although the model is structurally complex for vehicle detection, an alternative approach is presented in [20], which proposes a compact and separable feature learning technique for vehicle identification. This approach yields an accuracy rate of 80.2%. Furthermore, [21] and [22] introduces an enhanced YOLOv5 model for vehicle detection, employing the Flip-Mosaic algorithm to enhance network perception for small objects. The investigation, conducted on the BITs dataset, results in an impressive mean average precision (mAP) improvement to 95%.

Moreover, [23] and [24] incorporates ShuffleNetv2 and GhostNet into YOLOv5 to enhance vehicle detection. The utilization of a convolution block module results in improved detection accuracy with greater efficiency. In the context of overcoming occlusion challenges, [25], [26] introduces the EfficientLiteDet model, which addresses the occlusion of targets due to fewer targets. This model is tested on five different datasets and pedestrian detection, surpassing Tiny YOLOv4 by 2.4% in mean average precision (mAP). The model is trained using supervised learning, which involves classifying objects, regression, and predictions on labeled datasets. A prominent approach for image classification is the extraction of features from raw images, followed by training the model using the extracted feature set [27], [28]. In some cases, specific learning algorithms have proven to be highly effective in computer vision for vehicle detection and classification. For instance, [29], [30] employs the DenseNet121 model in a single dataset, outperforming MobileNetV2, ResNet-50, VGG 19, Inspection-ResNet-V2, Xception, and Inception-V3, achieving an impressive accuracy score of 95.14%. Additionally, aside from vehicle classification (VC), there are efforts to detect and address illegal parking with a remarkable accuracy rate of 99.41% and an increased number of detected violations. These endeavors employ the YOLOv4 and DeepSORT models for vehicle violation detection, as well as YOLOv4 + Tesseract for number plate detection and extraction [31], [32]. Furthermore, [33] and [34] explores various research on a 3-layer architecture designed for detecting vehicles from video frames. Each layer performs specific tasks, including feature mapping, sliding, and bounding box creation that contains vehicles.

Additionally, [35] and [36] introduces a novel framework architecture for vehicle classification (VC) that delves into vehicle model, type, and fuel identification. This framework leverages microelectromechanical systems and machine learning, founded on the principle of privacy-by-design, achieving an impressive accuracy rate exceeding 90%. In [37] and [38], explores the application of lightweight graph-based cryptography to address authentication and security challenges within Intelligent Transportation Systems (ITS). The optimization of machine learning models is tackled, with the establishment of six different models. Notably, Logistic Regression (LR) outperforms multinomial NB, GB, RF, DT, and SVM in terms of accuracy. In [39] and [40], a combination of K-means clustering and KLT tracker is

TABLE 1. Comparison of contemporary vehicle classification datasets including proposed dataset.

Dataset	Year	Classes/Images	categories	Model
BIT-Vehicle UA-DETRAC (1)	2021	6/10,051 4/8250	4	FasterR-CNN, YOLOv4, Efficient Det, YOLOv4_AF
ESCAPE NuScene (2)	2022	5 4	4	FasterR-CNN, COCO, VGG16
FLIR thermal FLIR RGB MB7500 KITTI (4)	2023	5/7500	-	FasterR-CNN, YOLOv5
SRM2KTR	**2023**	**1,038,115**	**10**	**Sparse coding, SIFT + FV, AlexNet and VGGNet**

integrated into YOLOv2 to enable vehicle counting, detection, and speed estimation. This enhancement results in a 5.5% improvement in recall accuracy and an average time improvement of 93.3% across various sequences. Similarly, [41] and [42] presents a novel YOLT technique for detecting vehicles from aerial imagery. This model achieves a mean average precision (mAP) of 80% and effectively addresses challenges related to category variation, contrast scalability, and complex scenery within dominant resolution processing. Using UAV video data, [43], [44] demonstrates the identification of vehicles through deep learning techniques, specifically SSD and Faster CNN. The video data is captured using a DJI Phantom 3 Professional drone with a resolution of 3840 $\times$ 2160, yielding a remarkable vehicle detection accuracy rate of 96.49%. The varying shapes and structures of roads, which can impact the accuracy of vehicle detection, are addressed in [45] and [46] with the proposal of YOLOv7-RAR. This model aims to reduce errors in the detection of random features and significantly enhance processing speed, achieving up to 160 frames per second (FPS) and an Average Precision (AP) of up to 56.8%. Feature extraction for vehicles in low-light situations poses a significant challenge in machine learning models. In response, [47], [48] conducts experiments using a trained model named YOLOv3, achieving a mean average precision (mAP) of 72.8. However, the model excels at identifying cars but faces challenges in recognizing buses and trucks. To improve vehicle model detection in low illumination conditions, [49], [50] adopts the YOLOv5 model with the assistance of the k-means clustering algorithm.

The performance of vehicle detection using modified YOLO and Faster CNN has been evaluated on three different datasets, resulting in accuracies of about 94.00%, 94.22%, and 95.67% [51], [52]. In recent technology, [53], [54], [55] parallel edge AI is implemented for multi-task ITS, in which the data is preprocessed with parallelism for real-time vehicle detection with an accuracy of 95% in buses and cycles, 90% in cars, and 87% in truck classification [56], [57], [58]. The CatBoost algorithm is used to identify the internal categorical data, which slows down the training time while classifying the vehicle images from the image dataset [59], [60], [61]. Table 1 displays the statistics of existing vehicle classification benchmarks jointly with SRM2KTR. The size of SRM2KTR in both model and images surpasses the size of the existing dataset. Although there are a few datasets, such as SOCAR with greater models, the quantity and quality of images for unique models are less. The literature survey reveals certain limitations in existing datasets [62], [63]. For instance, the GRAM-RTM dataset does not provide vehicle type classification. Even large-scale datasets like MIO-TCD face significant challenges in classifying vehicle images when employing models such as ImageNet, COCO, AlexNet, and Inception-V3. In contrast, the SRM2KTR dataset offers a comprehensive solution, encompassing both vehicle models and images. This versatile dataset is compatible with various models, including Sparse coding, SIFT + FV, AlexNet, and VGG-Net. However, existing datasets encounter bottlenecks during the preprocessing stage of vehicle image classification. These challenges arise from the extensive multiclass variance in vehicle images, as well as the scattered grayscale intensities. Moreover, distinguishing between vehicles of similar sizes and colors can be challenging. Noise and irrelevant features may also persist after feature extraction. The substantial multiclass variance and scattered grayscale intensity further complicate the accurate classification of vehicles within large-scale datasets.

Consequently, the proposed methodology aims to overcome these challenges, specifically addressing the issues of scattered grayscale intensities and high-dimensional features through an algorithm. This approach results in a remarkable accuracy rate of 98.8% in vehicle classification, particularly using the XGBoost model, on a large-scale dataset.

III. XGBOOST ALGORITHM

The eXtreme Gradient Boosting (XGBoost), an ensemble algorithm, has been widely preferred for image classification. In recent times, this algorithm is considered to be the most productive technique for vehicle classification. These algorithms are much extendable complete tree boosting for classification and regression [64], [65]. The specified dataset is taken in the form of dimensions. These classification and regression are considered in terms of decision trees. The selected map is fed to the node of the tree. The count and score are taken into account of calculation. The nodes are ordered and investigated the factors to obtain the optimal model. The model is then used for XGBoost modeling. Initially,

$$Obj(t) = \Sigma_{a=1}^{n} B(x_i, x'_i) + \Sigma_{a=1}^{t} \Omega(y_i) \tag{1}$$

$$\Omega(y_i) = \alpha T + 1/2\beta \Sigma_{a=1}^{t} W_j^2 \tag{2}$$

In the equation 1, x_i and x'_I are given as real and predicted value of deviation square loss function. Regularization term is mentioned as $\Omega(y_i)$. Splitting tree co efficient is given by the α, β. The predicted value is given once the iteration is stopped

$$C_i^{'(t)} = C_i^{'(t-1)} + d_t(b_i) \tag{3}$$

Objective function are expressed as

$$Obj(t) = \Sigma_{i=1}^{n} B(x_i, x'_i) + f_i(b_i) + \Omega(y_i) \tag{4}$$

Loss function depend on Taylor series with nearest rate and accuracy.

$$Obj(t) = \Sigma_{i=1}^{n} [E_i - [E_i^{'(t-1)} + f_t(x_i)]]^2 + h \tag{5}$$

The Obj(t) calculate the node to minimize loss function.

IV. VEHICLE CLASSIFICATION USING XGBOOST ALGORITHM

In this section, a comprehensive explanation of the FPGA implementation for vehicle classification using the XGBoost algorithm is provided. The process initiates by collecting vehicle images from the designated dataset, capturing them at different time frames and angles. Notably, this dataset encompasses vehicle images under varying illuminance conditions and angles, thereby facilitating the validation of real-time processes. The dataset contains vehicle images that vividly depict real-world scenarios, offering invaluable support for both scholars and scientists. Researchers can employ this dataset to evaluate the performance of their existing deep learning models, particularly those trained on diverse datasets. It proves especially beneficial for scholars engaged in the development of vehicle type and model classification systems, enabling them to train and assess their models under real-time conditions. Within this dataset, all vehicle images are meticulously annotated and categorized into ten distinct classes based on vehicle type and model. The schematic representation of the proposed vehicle classification approach employing the XGBoost algorithm is illustrated in Figure 1.

A. DATA ACCESSION AND PRE-PROCESSING

The initial steps of the data collection process involved recording videos using a high-quality camcorder designed for vehicles. These videos were captured at varying frame rates and under different environmental conditions, including day, night, rain, and fog.

In this paper, real world dataset is utilised for evaluation. The dataset consist of vehicle images for classification and identification. SRM2KTR is a large-scale containing two-wheeler, three-wheeler, four wheeler, auto, tempo, jugad, car, pick up, bus, truck, tractor, backhoe, defense vehicle and equipment vehicle includes 1,038,115 images of 28,000 identifies. These images are picked under various vehicle viewpoint and climate condition in daylight, evening and night. Some identifies are used for training and rest for testing. It is taken under complex environments. The camera used was the SA-TATYA PZCR50ML42CWP, equipped with a 5MP Pan-Tilt-Zoom Camera featuring 42x Optical

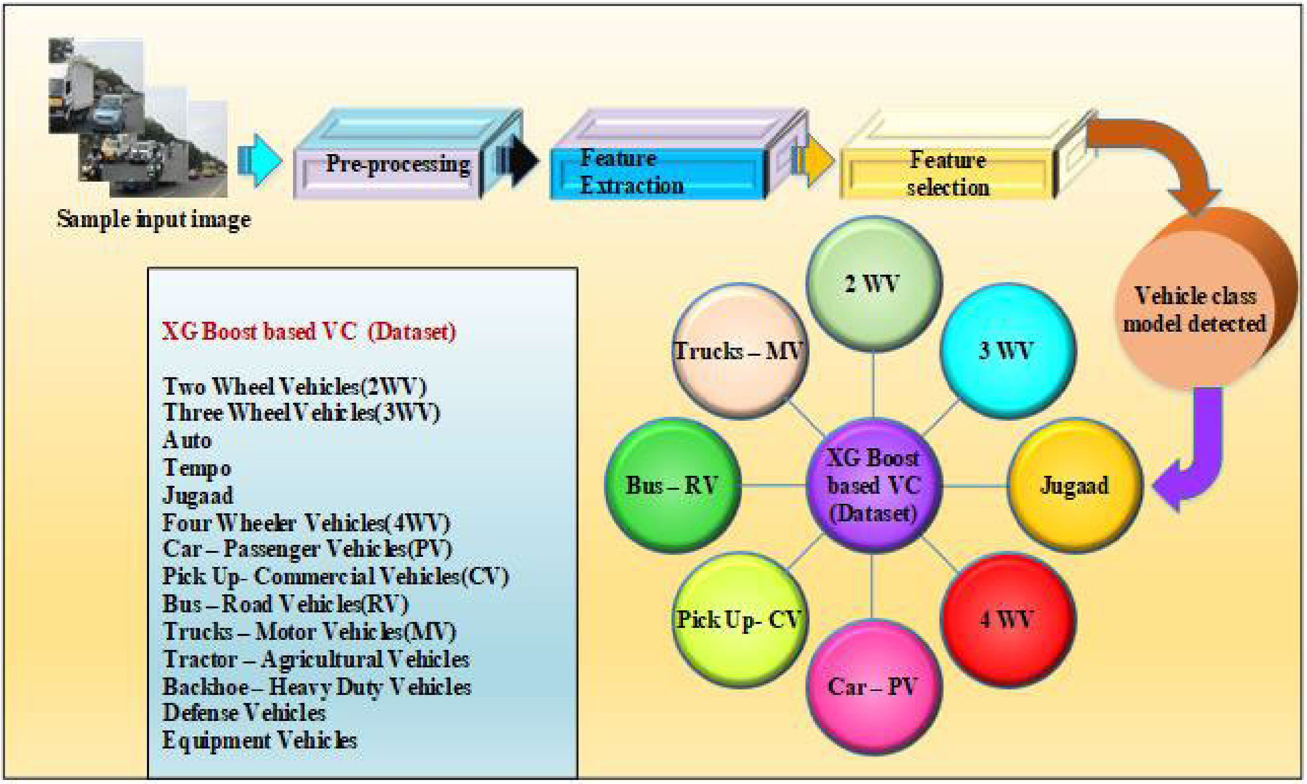

FIGURE 1. Overall architecture of the proposed for vehicle classification.

Zoom and powered by the Wide Dynamic Range (WDR) algorithm. The video recordings were conducted on the main National Highway (NH) in front of SRM IST, Kattankulathur, following the necessary permissions for video capture. The recorded videos were subsequently divided into individual frames, with a one-second interval between each frame. To ensure data quality, duplicate images or videos of the same vehicles were manually removed. Moreover, most background elements were eliminated to safeguard privacy and enhance security, leaving only the vehicle images intact. Subsequently, these curated vehicle images were organized into various datasets, with each dataset being categorized into different folders. Each folder was labeled to indicate the type and model of the vehicles contained within. To protect the personal details of vehicle owners, particular attention was given to keeping the number plates intentionally unfocused and some with owner permission the licence plates is focused. Out of 1,038,115 images of 28,000 categories only 75,436 images with 10 categories are considered. Following these comprehensive annotations, a split of 60% for training and 40% for testing was employed. This balanced division enabled the evaluation of various machine learning models. Thus SRM2KTR dataset are substantial, comprehensive, diverse, and valuable for diverse tasks. The overall process of creating the SRM2KTR dataset is visually depicted in Figure 2. Following the dataset collection, the importance of a pre-processing phase becomes evident. Attempting to apply raw data directly to any classifier model often yields suboptimal accuracy in vehicle classification. Therefore, pre-processing techniques are introduced to enhance the data. In this study, a combination of randon and wavelet transform techniques is employed during the pre-processing stage to augment and compress the images. Initially, the dimension of the images is computed, and the background is subtracted. Subsequently, the images are normalized and standardized, and the transformation process is utilized to extract image edges. Randon transform proves effective in edge detection. However, since it does not provide extensive information about patterns, wavelet transform is incorporated into the process. This combination of randon and wavelet transforms serves to reduce the scattering of grayscale intensity. Moreover, these pre-processing techniques assist in mitigating noise within the patterns and contribute to image compression, facilitating subsequent feature extraction processes. In the Figure 3 and 4 show the flow diagram and stimulation process of randon and wavelet transform. comprehensive annotations, a split of 60% for training and 40% for testing was employed. This balanced division enabled the evaluation of various machine learning models. The overall process of creating the SRM2KTR dataset is visually depicted in Figure 2. Following the dataset collection, the importance of a pre-processing phase becomes evident. Attempting to apply raw data directly to any classifier model often yields suboptimal accuracy in vehicle classification. Therefore,

FIGURE 2. A novel dataset named SRM2KTR dataset containing various types of vehicles with different classes.

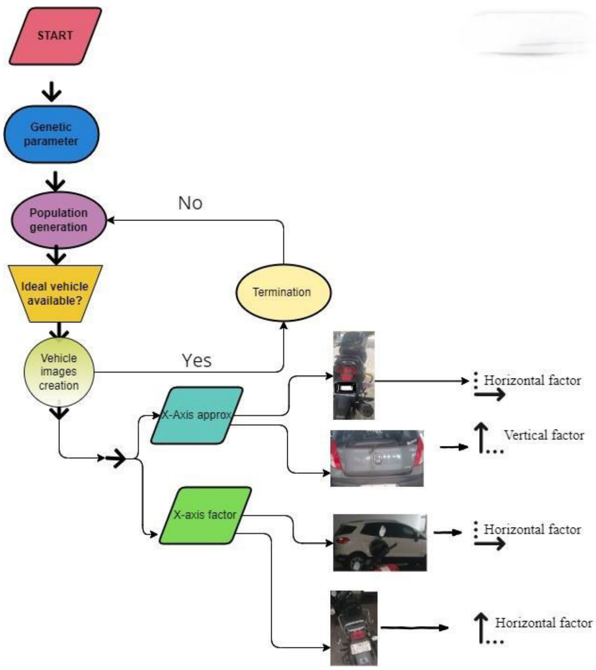

FIGURE 3. The workflow diagram of preprocessing images in which the images are augmented and compressed.

pre-processing techniques are introduced to enhance the data. In this study, a combination of random and wavelet transform techniques is employed during the pre-processing stage to augment and compress the images. Initially, the dimension of the images is computed, and the background is subtracted. Subsequently, the images are normalized and standardized, and the transformation process is utilized to extract image edges. Random transform proves effective in edge detection. However, since it does not provide extensive information about patterns, wavelet transform is incorporated into the

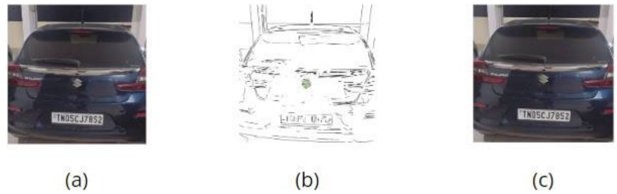

FIGURE 4. The result of preprocessing methods using randon and wavelet transform for real time images. (a) implies the raw images to be feed into preprocessing techniques (b) Shows the result of randon transform in which the edge of the vehicles images are highly bedrock for vehicle classification (c) The result of the wavelet transform in which the output of the randon wavelet is store the images in various scales of resolutions.

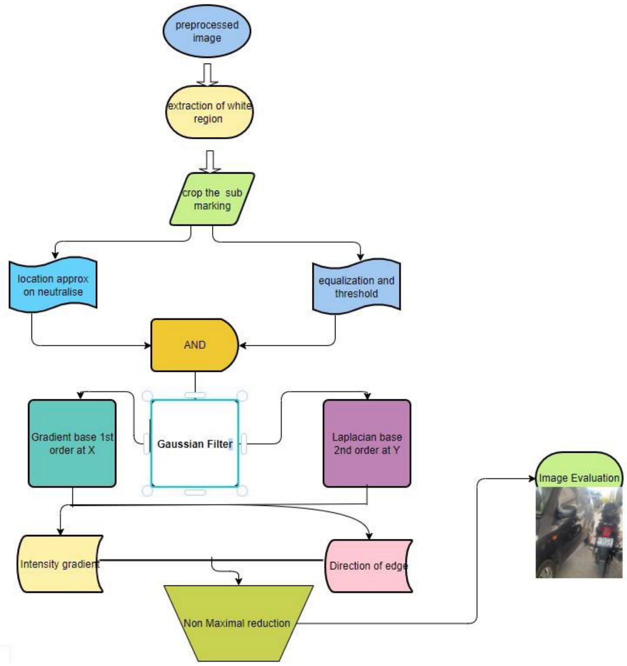

FIGURE 5. The workflow diagram of feature extraction from preprocessed images in which the feature of the vehicle images are extracted for feature selection processes.

process. This combination of random and wavelet transforms serves to reduce the scattering of grayscale intensity. Moreover, these pre-processing techniques assist in mitigating noise within the patterns and contribute to image compression, facilitating subsequent feature extraction processes.

B. FEATURE EXTRACTION

The image features are represented in numerical form, providing a comprehensive definition of the characteristics inherent to the vehicle image.

These features serve as the basis for structural and meaningful depiction. Grayscale images are acquired and subsequently combined, feeding into the model. However, it's essential to note that these images are in a high-dimensional format. Within this high-dimensional format, a set of 50 statistical features is extracted. These features encompass characteristics such as correlation, dissimilarity,

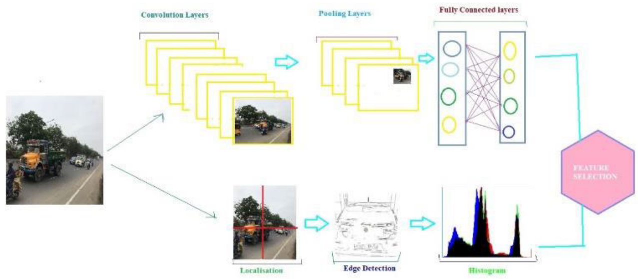

FIGURE 6. General block diagram of feature extraction for vehicle classification using edge and region base segmentation.

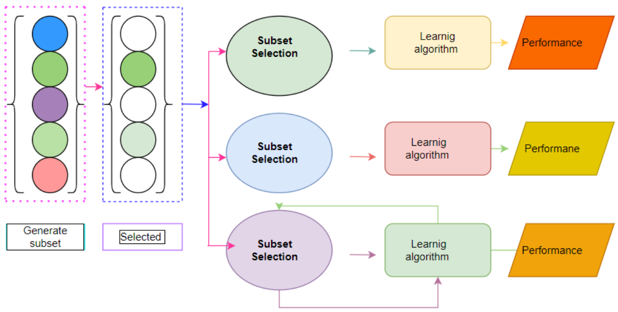

FIGURE 7. General flow diagram of feature selection processes for vehicle classification using embedded method.

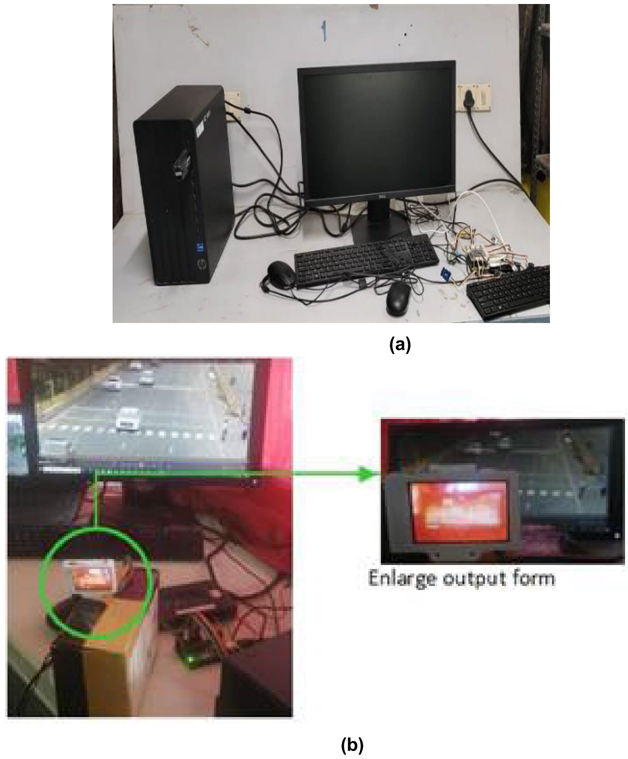

FIGURE 8. Hardware setup for vehicle classification using FPGA board (a) shows the general hardware setup (b) shows the real time video for vehicle classification using FPGA board.

and non-uniformity. To more accurately represent the texture of the image, these characteristics are amalgamated using edge and region-based segmentation techniques. This approach involves the segmentation of vehicle feature images based on similar pixel criteria, effectively reducing dimensionality. Through this process, variations in intensity levels and the discontinuity of edges are effectively detected and interconnected as part of the feature selection processes. In Figure 5 and 6, show the general workflow and block diagram of extraction technique.

C. FEATURE SELECTION

Feature selection is a pivotal aspect of machine learning, as it strives to identify a concise subset of features that are both essential and accurately represent the relevant information present in each dataset. This proposal introduces an embedded technique that assesses the significance of features and subsequently selects the most pertinent ones. These selected features are then supplied to the trained model, enhancing the accuracy of vehicle image classification. The general flow diagram is illustrated in Figure 7.

D. CLASSIFICATION

Following the feature selection process, the subsequent step is classification, a fundamental task within the classifier model. After the selection of features via the embedded technique, these features are utilized to train a machine learning (ML) model. Notable ML models include the Multilayer Perceptron (MLP), Support Vector Machines (SVM), Naïve Bayes (NB), K-nearest neighbors (KNN), and XGBoost Classifier. The images, labeled ac-cording to their type and model, are used to train the ML model. Subsequently, the trained model is evaluated against a test dataset to gauge its performance. Thus, the combined utilization of feature selection processes and model training, particularly employing the XGBoost algorithm, contributes to the identification of valuable features and serves to enhance the accuracy and overall performance of the ML model.

V. EXPERIMENT SET UP FPGA IMPLEMENTATION USING XGBOOST

The experimental setup for the FPGA implementation of Vehicle Classification (VC) using the XGBoost algorithm is visually depicted in Figure 3. The experiment entails the utilization of ten publicly available vehicle datasets, including VEDAI, DLR-3K, DOTA, Real-world fuel efficiency, NYS Electric Vehicles Data, CMS, Monthly HELP, Motorized access trails, SRM2KTR, and the 2023 Cars dataset. This extensive experiment was con-ducted using an Intel® Xeon® Processor E3-1225 v5 with 8M Cache and a clock speed of 3.30 GHz. The system is equipped with a 64GB memory. The dataset employed for this experiment comprises 43,224 images for training and 32,212 images for testing, with each image labeled according to its vehicle type and model. In the classification process, the XGBoost algorithm is configured with specific parameters, including a learning rate of 0.5, a maximum of 100 leaves, and a maximum depth of 20. The model is designed to classify vehicles based on their type and model, and it is trained using all relevant features. To facilitate the processing of images and vehicle classification, the algorithm is implemented on an FPGA board known as myRIO. The myRIO board manages the image processing flow and rapidly retrieves images while categorizing them by vehicle type. The classification of vehicles is achieved with precision using a huskylens camera. Furthermore, the experiment encompasses various challenging conditions, including scenarios involving low light, adverse weather conditions, vehicles of the same color but different types, identical vehicles with varying colors, and occlusions. The hardware setup for this experiment is illustrated in Figure 8.

A. FPGA DESIGN FLOW USING MY RIO

To implement the classification of vehicles using the XGBoost algorithm on an FPGA, the myRIO platform is employed. This choice is made due to constraints related to the size of the vehicle. The myRIO-1900, developed by National Instruments, serves as the control system for executing programs in mechanical and electronic systems. It is a compact and specialized solution designed to support the educational needs of research scholars, academics, and scientists.

The myRIO platform features an FPGA processor with a Xilinx Z-7010 processor operating at a frequency of 667MHz. The maximum power consumption of this system is 14W, and it is equipped with a 256MB memory. Once the necessary software is installed, the LabVIEW window becomes readily available for use in conducting the experiments and implementing the vehicle classification system.

When the toggle switch is turned on, the vehicle is identified, and as it crosses the system's field of view, an LED indicator is illuminated. On the other hand, when the switch is turned off, the system initiates the extraction of vehicle information and proceeds to classify the vehicle based on its type, color, categories, and class. The illuminated LED indicates the system's active condition during vehicle crossing, and it returns to an off state once the vehicle has completed its passage. The Huskylens camera is an integral part of this system, continuously recording real-time images or videos. If a vehicle is detected, the system checks its memory to verify whether the vehicle's features match those of a trained vehicle. If the vehicle is recognized as trained, the system displays information about its type, color, and class in a serial or sequential manner.

Alternatively, if the vehicle is not recognized, it is associated with another set of features from the trained database, thus identifying the vehicle based on assigned factors such as color pattern, class, and model. This configuration is typically executed through a programming interface where parameters like intensity and color are defined. The cameras are equipped with an algorithm that predicts the vehicle's image and identifies its color, model, or class. The entire process is visually represented in the flowchart depicted in Figure 9. This research is conducted by merging hardware and software components. In the hardware segment, the Huskylens module is connected to the FPGA board. The performance of the classifier is evaluated using a set of metrics, and Table 2 provides an overview of the evaluation metrics for the classifier when implemented on different datasets, including the proposed dataset. The results are compared to those of various classifiers using different datasets, demonstrating that the proposed model achieves similar performance standards but with reduced processing time, setting it apart from existing models and datasets. In the Table 2, SRM2KTR dataset have better evaluation metric with XGBoost classifier nearly 98.81%. The reduction in grey scale intensities and

TABLE 2. Evaluation metric of the classifier implemented in 10 datasets including proposed dataset.

Dataset	CLASSIFIE R	Acc(%)	Prec(%)	Rec(%)	F1(%)
VEDAI	SVM NB KNN XGBoost	86.2 75.2 69.5 90.2	86.1 75.12 69.52 90.1	86.24 75.08 69.45 90.5	86.1699 4 75.0999 9 69.4849 90.2995
DLR-3K	SVM NB KNN XGBoost	90.6 85.6 75.3 95.5	90.64 85.62 75.38 95.47	90.58 85.74 76.35 95.54	90.6099 85.6799 6 75.8619 95.5049 9
DOTA	SVM NB KNN XGBoost	89.4 80.6 78.2 94.6	89.34 80.68 78.32 94.58	89.21 80.23 78.55 94.56	89.2749 80.4543 7 78.4348 3 94.57
Real-world fuel efficiency	SVM NB KNN XGBoost	86.7 84.2 72.3 90.8	86.75 84.23 72.35 90.82	86.6 84.3 72.5 90.84	86.6749 4 84.2649 72.424 90.83
NYS Electric Vehicles Data	SVM NB KNN XGBoost	76.5 70.512 69.91 89.7	76.54 70.5 69.5 89.714	76.65 70.62 70.1 89.81	76.5949 70.5599 5 69.7987 89.7619 7
CMS	SVM NB KNN XGBoost	82.3 79.94 75.8 89.9	82.1 79.84 75.85 89.94	82.12 79.841 75.849 89.95	82.11 79.8405 75.8495 89.945
Monthly HELP	SVM NB KNN XGBoost	92.6 89.95 85.7 97.574	93.1 89.91 86.5 97.8	93.2 90.01 85.4 97.2	93.1499 89.959 85.946 97.499
Motorized access trails	SVM NB KNN XGBoost	86.5 84.3 78.2 90.48	86.54 84.24 76.8 91.244	86.45 84.35 77.77 91.54	86.4949 84.294 77.2819 6 91.3917
2023 Cars dataset	SVM NB KNN XGBoost	89.6 73.4 73.02 92.7	89.61 73.54 73.5 93.75	89.57 74.65 73.56 94.75	89.59 74.090 73.529 94.24
SRM2KT R	**SVM** **NB** **KNN** **XGBoost**	**98.21** **97.512** **97** **98.82**	**98.12** **97.51** **97.01** **98.81**	**98.13** **97.5** **97.1** **98.81**	**98.125** **97.505** **97.05** **98.81**

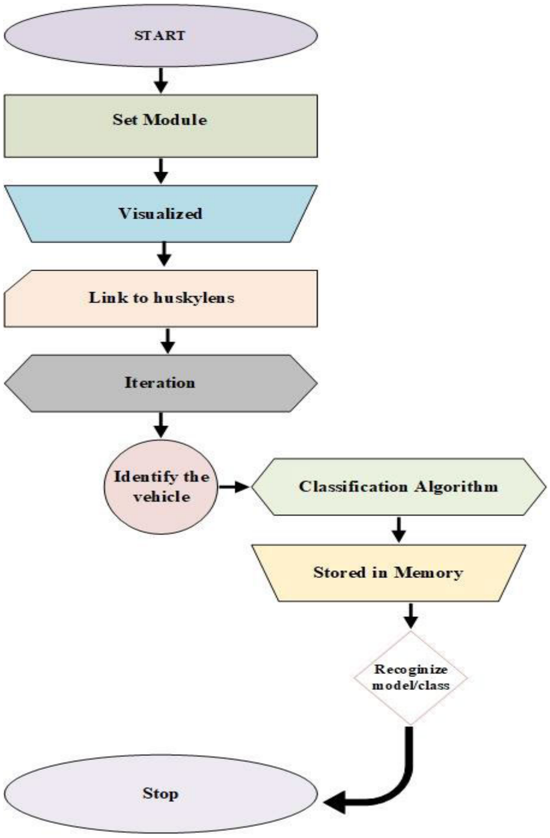

FIGURE 9. Flowchart of FPGA implementation of vehicle classification using XGBoost Algorithm.

FIGURE 10. Sample vehicle images under dark conditions.(a)shows the raw images under dark environment from real time videos (b) The classes of vehicle images are highlighted with red boxes.

high dimensional data make the classifier much stronger in classification accuracy. In case of SVM classifier, it have better classification rate of 2% when compared to the NB classifier. NB classifier gain 1% accuracy when compared to KNN. KNN required lot of memory for computation resources and also it take long processes for training time.

FIGURE 11. Sample vehicle images under different weather conditions such as fog, mist and rain.

FIGURE 12. Sample vehicle images of same colour but different vehicle (left). Similarly, same vehicle but different colour (right).

FIGURE 13. Sample vehicle images with occlusion condition.

VI. RESULTS AND DISCUSSION

In this section, the paper presents the performance of the proposed framework under various conditions, including vehicle images captured in dark conditions (Figure 5), different weather conditions (Figure 6), a wide range of vehicle colors and types (Figure 7), and scenarios involving occluded vehicles (Figure 8).Figures 9 illustrate the mean Average Precision (mAP) at Intersection Over Union (IOU) thresholds ranging from 0.6 to 0.98, as well as box loss, class loss, and object loss resulting from the proposed training conducted

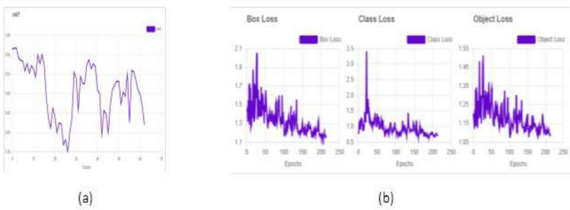

FIGURE 14. Output waveform of classification loss for classifying vehicles.

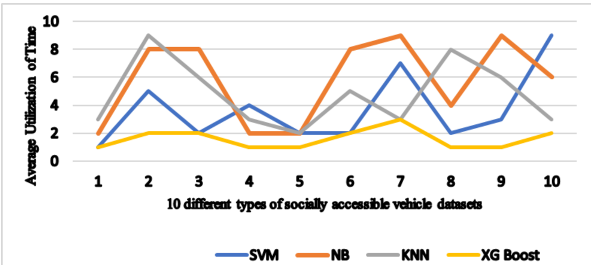

FIGURE 15. Time utilization for each dataset accessible vehicle classification.

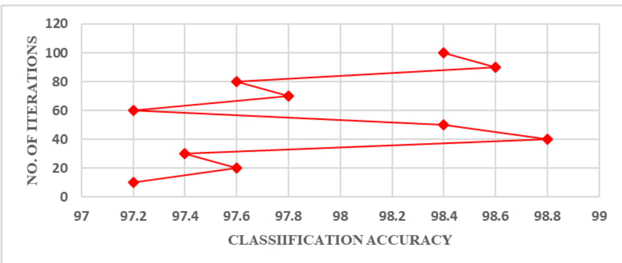

FIGURE 16. Classification accuracy under different iterations.

over 70 epochs. These metrics are calculated based on the validation set while training with the extensive dataset. The obtained results show that the mAP reaches 80% at a 0.6 IOU threshold, while the highest IOU score is 40%. The precision reaches 90%, indicating that true positives are significantly higher compared to false positives. The recall rate is 80%, reflecting a large number of true posibtives. The box loss measures the algorithm's ability to accurately locate the vehicle within the bounding box, while the object loss represents the identification of vehicles within the region of interest. The class loss pertains to the precise classification of vehicle types. These loss metrics collectively reflect the quality of vehicle image predictions from the dataset.

Furthermore, the proposed model shows substantial improvements after approximately 35 to 40 epochs, reducing the training time by 50%, as indicated in Figure 10. In comparison to SVM, Naïve Bayes, and KNN, the proposed method offers significantly reduced training times, taking only 2 milliseconds. This is in contrast to the computational time consumed by real-time processing, which involves around 4,000,000 instances, while SVM requires considerably more time, even under 1,000,000 instances when implemented on a Graphical Processing Unit (GPU). Figure 11 visually represents the classification accuracy, demonstrating that an ac-curacy rate of 98.8% is achieved after 40 iterations, underlining the effectiveness of the proposed model. Figure 12 to Figure 16 represents the different data sets and predicted accuracy using the proposed approach.

VII. LIMITATIONS AND FUTURE SCOPE

While our work demonstrates significant advancements in vehicle classification using XGBoost, limitations exist. These include hardware complexity, potential environmental variability, generalization to unseen data, and resource consumption during training. For future work, we propose enhancing hardware implementations, addressing extreme environmental conditions, expanding dataset diversity, exploring advanced ensemble techniques, optimizing for real-time processing, and conducting field deployments for practical insights. By tackling these limitations and pursuing these future directions, we aim to advance vehicle classification research and contribute to the development of robust real-world applications. For future work, the algorithm can be applied in hardware implementations within complex environments. Moreover, advanced ensemble techniques may be employed to train extensive datasets. Predictions across various categories of vehicle identification, classification, and localization within real-time vehicle images should be accomplished with faster computational speeds.

VIII. CONCLUSION

This paper introduces the SRM2KTR dataset, distinguished by its substantial volume, comprehensive class coverage, and wide-ranging diversity of vehicle images compared to existing datasets. Serving as a valuable benchmark for Vehicle Classification (VC), it aids researchers and scientists in diverse VC tasks such as identification, retrieval, recognition, segmentation, and cross-class retrieval due to its remarkable generalization capabilities. The primary focus lies on vehicle classification using the XGBoost algorithm to enhance accuracy, leveraging a large-scale dataset encompassing 75,436 images across 10 categories. The proposed methodology involves high-dimensional data reduction during pre-processing through random and wavelet transformations, alongside dimensionality reduction via region and edge-based segmentation.

Employing the ensemble algorithm XGBoost as the classifier for VC, chosen for its effectiveness in handling large-scale datasets and mitigating overfitting, various models including Sparse coding, SIFT + FV, AlexNet, and VGGNet are evaluated for efficiency. Experiments conducted on an FPGA board named myRIO, interfaced with devices controlling program flow, and Huskylens for vehicle classification based on various conditions including type, color, dark environments, poor weather, and occlusions.

Comparisons across various datasets and classifiers (SVM, Naïve Bayes, KNN, and XGBoost) highlight the effectiveness of the proposed algorithm, achieving a maximum accuracy of 98.8%. XGBoost's superiority is evident in its interpretation speed, reduced training time, higher true positives, fewer false positives/negatives, and more precise trained weight compared to traditional algorithms. Notably, features such as regression to address overfitting, parallel processing, handling missing values, cross-validation, and effective pruning make XGBoost a stable and efficient choice for VC. Execution on GPUs drastically reduces computation time, enabling real-time processing capabilities, a significant advantage over CPU-based models like SVM.

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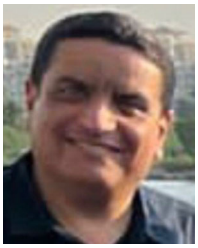

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