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Research Article

Improving Traffic Sign Classification with Convolutional Neural Networks

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Abstract

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Precise classification of traffic signs is a basic and intrinsic element in the development of autonomous driving and intelligent transportation systems. This is due to its outstanding role in reducing traffic accidents and improving road safety. The problem revolves around the difference and variation in visual similarity between the categories. As well as in the photographic conditions. This makes the task more difficult for traditional models. In this paper, we present a deep learning approach that combines pretrained deep models in high-precision feature extraction with a unified multilayer classifier (MLP). Able to use these features very efficiently. Regarding the dataset, the proposed framework relied on the GTSRB dataset, which includes more than 50 thousand images and 43 categories. Subsequently, a standardized preprocessing operation is performed, including image normalization and resizing according to ImageNet values. This research uses several diverse deep learning models, including DenseNet121, GoogleNet, ResNet18, ResNet50, MobileNetV2, VGG19, and EfficientNet-B1, to extract high-precision features. Performance is evaluated using the following metrics: accuracy, recall, precision, and F1-score. The study concluded that using DensNet121 features with the proposed classifier we used in our research paper achieved an accuracy of 99.41%, surpassing many previous studies. The results demonstrate that the proposed model achieves outstanding performance and effectively balances high accuracy and computational efficiency, making the model practically applicable in autonomous driving environments.

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1. INTRODUCTION

Self-driving systems and smart vehicles have become among the most prominent trends today, aiming to build safer traffic environments for both vehicles and pedestrians [1]. Traffic sign recognition is a key component of these systems, playing a fundamental role in helping vehicles make the right decision in real time [2]. This, in turn, reduces accidents resulting from human error [3]. The autonomous driving system relies primarily on the effectiveness and capability of the visual recognition model on traffic signs under various imaging conditions [4]. Recent years have witnessed remarkable progress in the fields of deep learning and computer vision. This has enabled new possibilities for handling highly complex images and extracting high-resolution representational features [5]. Convolutional neural networks (CNNs) have demonstrated high-efficiency in this area, becoming the cornerstone of advanced visual recognition systems [6]. Furthermore, some challenges remain. Individual models struggle to strike a balance between computational efficiency and accurate classification ratios when implemented in real-world environments where they require limited resources and high-performance speeds [7]. The high degree of similarity between traffic sign categories makes it difficult to distinguish between them, requiring careful processing of precisely defined visual features [8].

Based on these challenges, this research aims to improve the theoretical and methodological framework that combines the characteristics of pre-trained models and the capabilities of a multi-layer classifier to achieve high-precision classification[9]., The proposed model is based on using the representational power of well-known deep models such as DenseNet121, ResNet18, ResNet50, MobileNetV2, VGG19, EfficientNet-B1, and GoogleNet to extract features from the GTSRB dataset., This collection contains over 50,000 images and 43 categories. These categories are characterized by a diversity of shooting and photographic conditions, which contributes to model training and generalizability. The methodological framework of this research is based on the use of features extracted from pre-trained deep models into a unified multi-layer classifier (MLP).

It also uses the Adam algorithm with the adoption of organization techniques, such as dropout and batch normalization. StepLR dynamic learning scheduling to adjust the learning rate. This design seeks to achieve a highly precise balance between training stability and convergence speed and the quality of the final results. The performance of the proposed methodology was evaluated using the following criteria: accuracy, precision, recall, and F1-score. Measure the model's performance from several aspects and ensure a complete evaluation. This research work aims to build and improve a classification model. Capable of handling visual fluctuations in GTSRB data set images. resulting in a computationally efficient and highly accurate model that can be implemented in practice. Furthermore, a comparative analysis is presented demonstrating the efficiency of the proposed model in relation to key previous studies. This work also aims to strengthen the understanding of the relationship between the complexity of the structural model and the number of its parameters. This, in turn, contributes to providing scientific guidance for subsequent studies in building a model with more advanced analytical capabilities. The most significant contributions of this research work are as follows:

1 - This research paper presents a working model that includes several pre-trained deep models. This model extracts high-precision features, which in turn lead to accurate and highly efficient classification, thus improving the model's performance.

2- Developing a unified multilayer model. This model processes the features extracted from the models and achieves a balance between computational efficiency and accuracy. This allows its use in real-world applications.

3- The proposed methodology is tested using the following metrics: precision, recall, accuracy, and F1-score and is compared with previous studies.

This research work demonstrates a systematic framework containing the following sections. The second section shows the relevant previous works. The third section presents the systematic approach adopted in the study. The fourth section explains the results and compares them with previous work. The fifth section deals with restrictions and future actions. Section 6 discusses the conclusions and contributions.

2. RELATED WORKS

This section presents the most important studies in this research area. It focuses specifically on results, databases, contributions, publication year, and algorithms used. Modern scientific research in traffic sign recognition has benefited from machine learning strategies and techniques, as well as deep learning. The study [10] discussed reducing the level of high-cost errors in visual recognition by building a CNN supported by rejection sampling with cost-loss tasks. The model was implemented using a LISA database and achieved an accuracy of 88.3%. The key contribution of this research paper is to reduce the error rate of expensive outputs. Much research has led to clear and profound developments in this area, particularly regarding traffic signals. The study [11] introduced some improvements. This was achieved by building an 8-layer CNN with a model framework (VGG16) (ResNet50). These models were implemented on a German traffic signal dataset ,and the accuracy achieved in this study was 96%. Study [12] considered one-time learning using (ConvNets). This study also used the GTSRB dataset and achieved an accuracy of 90.13%. Furthermore, the study [13] used the following models (VGG19) and (VGG16) and achieved an accuracy of 98.38%. The reason for this high accuracy is the combination of deep learning and machine learning techniques. The study [14] used CPTSD databases and achieved 83% accuracy. The GTSRB database achieved 98% accuracy. The model used was LeNet-5.

Based on previous improvements. Much scientific research has addressed learning structures for handling and recognizing traffic signs. The study [15] used Malaysian traffic signal data and(MTS), achieved an accuracy of 98.41% using CNN. This study combined accuracy and speed. This research paper [16] presented a CNN model using the following algorithm structure. KNN. This model framework was applied to the Chinese Traffic Signal Data Set and (CTSD) achieved an accuracy of 94.7%. It combined deep learning techniques with machine learning. Its most important contribution here is that it has developed a hybrid approach, which has achieved a clear and remarkable improvement. This study [17] applied to three types of datasets: the GTSRB, the Belgian traffic signal dataset, and the Chinese traffic signal dataset (TSRD). The accuracy achieved was 98.84%, 98.33%, and 96.16%, respectively. Four models were used: Ensemble Learning VGG16, ResNet50, and DenseNet-121. This indicates that the study employed a multi-model ensemble system. This study [18] used a deep learning model, a lightweight CNN. on two datasets: GTSRB and Belgium TS. The accuracy achieved was 98.41% for German traffic signals and 92.6% for Belgian signals. The number of parameters used by this lightweight model was only 2.61 million, and the response time was very fast. On the other hand, the study [19] used deep learning techniques and included more than one model: Custom CNN VGG16, ResNet-50, MobileNetV2, and finally the InceptionV3 model. The highest accuracy obtained from these models in this research paper was 91.55%. The Bangladeshi traffic signal dataset (BTSRB) was used. Notably, the most important contribution of this paper was the creation of the first Bangladeshi architectural dataset. Based on the general trend, to improve the interpretation as well as the structure of research at the moment. Efforts were devoted to subsequent research papers on the efficiency and clarity of the model. The study [20] achieved an accuracy of 91.25%. using German traffic signs. The study employed the following machine learning techniques: HUE, CALHE, YUV, HOG, and HOG. The most significant contribution of this research paper was the comparison of pre-treatment techniques. The study also proposed improvements to the techniques used. Project [21] demonstrated an accuracy of 97.53%, employing deep learning techniques, including the LeNet-5 model. The study also relied on a set of German traffic signs. Notably, it contributed to building a lightweight neural network while maintaining efficiency.

The study [22] deliberately used the Belgium Ts and German traffic signs sets. The accuracy achieved was 92.16% and 98.41%, respectively. It employed the following models: MSA, FFN, MobileNet, and EAs, in addition to other models. It introduced an innovative hybrid system combining EAT and EA engineering, achieving high performance and speed. Other researchers [23] have also applied their models to the Chinese traffic signal systems (CCTSDB) and GTSRB, using three models: LENet-5, RNN, and KNN. Note that the study achieved the following accuracy rates, respectively: 93.2% and, 86%. This paper modified the parameters of the LeNet-5 convolutional core. which led to an improvement in the network architecture of the model used. Some studies [24] used the Grad-CAM interpretation. In addition to the models used in this paper, such as NASNetMobile and EfficientNet. This model was implemented on three types of datasets: first, the Indian traffic signal dataset with(ITSD) an accuracy of 94.735%; second, the Belgian traffic signal dataset with 92.69%; and third, the German traffic signal dataset with 98.85%. The most important contribution of this paper is that it integrates explainable artificial intelligence techniques to obtain highly accurate and intelligent transport systems. On the other hand, [25] used artificial intelligence techniques (LE-CNN), depth-wise separable convolutions, and channel pruning. This methodological framework was implemented on a Saudi traffic signal dataset (ArTs). with an accuracy of 96.5%. This paper contributed to the development of a lightweight and fast (1.65 second) model that is very useful for real-time driving. The results [26] yielded an accuracy of 95.35% using German traffic signal datasets. This methodological framework was implemented using, three well-known and robust models: ResNet-18, CNN, and MobileNetV2. This study contributed by providing advice on choosing a model with high accuracy and speed. Of the three models used above. Table 1 represents a comprehensive summary of previous work in the field of traffic sign classification, arranged chronologically from 2020 to 2025. It shows the basic components of previous research papers.

Table 1: Summary of the literature on traffic sign classification

Study	year	Approach	Algorithms and techniques	Dataset	Reported accuracy (%)
[10]	2020	Deep Learning	CNN, cost-proportionate rejection sampling, and cost -sensitive loss functions	LISA	88.3
[11]	2021	Deep Learning	8-Layer CNN Model, Resnet-50, Vgg-16	GTSRB	96
[12]	2021	Deep Learning	One-Shot Learning, Transfer Learning, and ConvNets	GTSRB	90.13
[13]	2021	Deep Learning and Machine Learning	VGG16, VGG19, Random Forest, Neural Network	GTSRB	98.38
[14]	2021	Deep Learning	LeNet-5	GTSRB CPTSD	98 83
[15]	2022	Deep Learning	CNN	MTS	98.41
[16]	2022	Deep Learning and Machine Learning	Custom CNN, KNN, and normalization	CTSD	94.7
[17]	2023	Deep Learning	ResNet50, DenseNet121, VGG16, and Ensemble learning	GTSRB BTSD TSRD	98.84 98.33 96.16
[18]	2023	Deep Learning	Lightweight CNN	GTSRB BelgiumTS	98.41 92.06
[19]	2023	Deep Learning	Custom CNN, VGG16, ResNet50, MobileNetV2, InceptionV3	BTSRB	91.05
[20]	2024	Machine Learning	HOG, SVM, YUV, CLAHE, and HUE	GTSRB	91.25
[21]	2024	Deep Learning	LeNet-5	GTSRB	97.53
[22]	2024	Deep Learning	PVT, TNT, LNL, AlexNet, ResNet, VGG16, MobileNet, EfficientNet, GoogleNet, EAs, FFN, and MSA	GTSRB BelgiumTS	98.41 92.16
[23]	2024	Deep Learning	LeNet-5, KNN, and RNN	CCTSDB GTSRB	93.2 86
[24]	2024	Deep Learning	VGG16 / VGG19, ResNet50V2, MobileNetV2, DenseNet121 / DenseNet201, NASNetMobile, EfficientNet , XAI, LIME, Grad-CAM	GTSRB ITSD BTSD	98.85 94.73 92.69
[25]	2024	Deep Learning	LE-CNN, depthwise separable convolutions, channel pruning	ArTS	96.5
[26]	2025	Deep Learning	CNN, ResNet-18, mobileNetV2	GTSRB	95.35
[27]	2025	Deep Learning	DRL , CSO, and AGA	GTSRB	97.97
[28]	2025	Deep Learning and Machine Learning	OpenCV, LeNet, Federated Learning, and Federated Averaging	BTSCB	93.65
[29]	2025	Deep Learning	LieCConv, LG-CNN, and ANS	TT100K	97.8
[30]	2025	Deep Learning	VGG16, MobileNet, resNet5 $4	ETSR	97.91

Other works [27] have also addressed a slightly different research methodology. which achieved an accuracy of 97.97%? using German traffic signals (GTSRB) with the following deep learning: CSO, AGA, and DRL. This study contributed to improving training parameters and presented a hybrid framework combining three models. Furthermore, the study [28] used Belgium traffic light datasets (BTSCB). and combined machine learning techniques with deep learning techniques. Among the models used were Federated Averaging, LeNet, and OpenCV. This study contributed to providing a comparative analysis. And improving performance judgments and identification of Belgian traffic signals in difficult weather conditions, especially in rainy weather conditions. The study [29] applied specific models to the Chinese traffic signal data TsignghuaTancet 100K (abbreviated as TT100K) and, achieved 97.8% accuracy. Using deep learning techniques, including ANS, LieCConv, and the LG–CNN model. This research work contributes to proposing an engineering solution. To improve memory efficiency in the network, which allows for the recognition of traffic signals. The last study, which we will discuss in our research paper [30], had an accuracy of 97.91%, used the Ethiopian traffic signal dataset (ETSR), and dealt with the following deep learning models: ResNet-50, VGG16, and MobileNet models. His most notable contribution to this research study was the creation of the world's first data set concerning Ethiopian traffic signals. By reviewing previous works, it becomes clear that most studies relied on deep learning techniques in various forms, while some researchers resorted to combining them with traditional machine learning methods, such as SVM and Random Forest, to enhance performance. The GTSRB dataset has emerged as the most common reference, as most studies have relied on it, while other databases such as LISA, ETSR, TT100K, BTSD, TSRD, and Belgium TS have also been used. At the level of models, they varied between traditional networks, such as LeNet-5, and deeper and more modern models, such as ResNet, MobileNet, and DenseNet. With the introduction of interpretive techniques, such as XAI, Grad-CAM, and others aimed at reducing computational complexity, such as a lightweight CNN. Among the reviewed studies, three achieved the highest accuracy rates on the GTSRB dataset: study [15] with an accuracy of 98.85% using a combination of deep networks and visual interpretation techniques, study [8] with an accuracy of 98.84% using Ensemble Learning to integrate multiple models, and study [4] with an accuracy of 98.38% using a combination of VGG16, VGG19, and machine learning methods. As part of the technical expansion, the next section will present our proposed methodology that relies on convolutional neural networks (CNN) and the application of its improved models using the transfer learning mechanism., The study included the use of several well-established and widely used architectural structures in the field of computer vision, such as GoogleNet, VGG19, ResNet18, EfficientNet-B1, MobileNetV2, ResNet50, and DenseNet121., The performance of these models was compared with high accuracy on the traffic sign classification task with the most prominent published works in this field to, analyze the distinctive aspects and practical differences in the efficiency of distinctive feature extraction to, determine the most suitable model for real-world applications.

3. METHOD

In this section of the research, we present the scientific methodology followed in our research work. This is done by extracting high-resolution features using seven pretrained models and then building a multilayer classifier capable of classifying and distinguishing traffic signs. Note that we used the data set known as German traffic signals, abbreviated as GTSRB. We then conducted a pretreatment process, which included the use of normalization. The following models were used to extract features: DenseNet121, Mobilenetv2, EfficientNet-B1, GoogleNet, ResNet-18, ResNet-50, and VGG19. In the penultimate step, we built an MLP model that performs the classification process. Finally, we evaluated the performance of the framework using the following evaluation metrics: recall, precision, accuracy, and F1 score. Fig 1shows the proposed methodological structure.

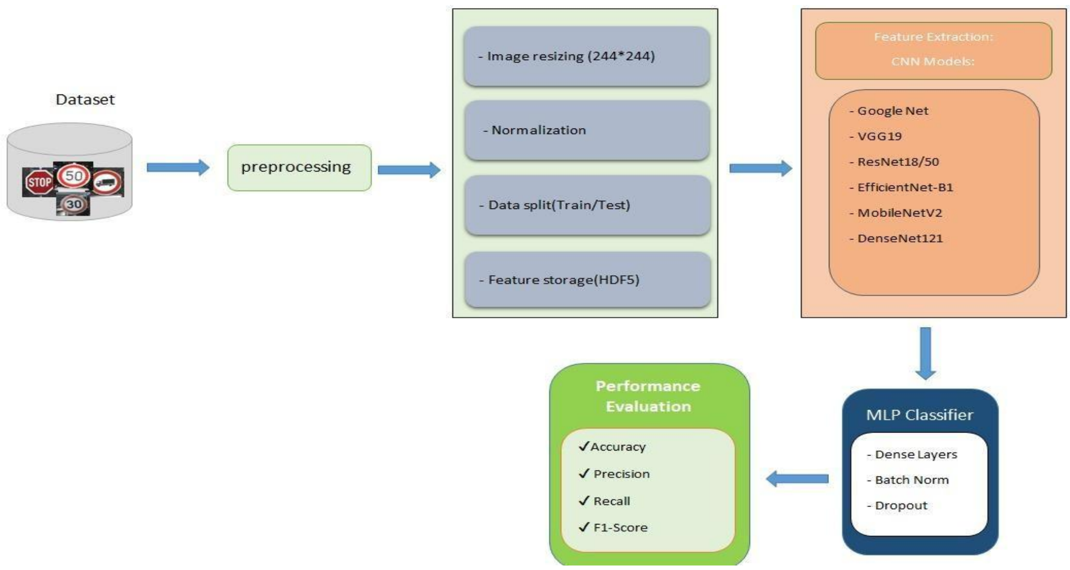


Figure 1: Proposed framework for traffic sign recognition

3.1 DATASET DESCRIPTION

In this scientific article, the German traffic signal dataset (GTSRB) was used because, this set contains a large number of images, with approximately fifty thousand images. In addition to containing 43 subdivided categories. These categories include, for example, stop signs, roadwork, child crossings, no entry, and other categories. Note that these images are diverse, and the weather conditions, situations, and angles at which the images were taken vary. This dataset has been used in numerous research papers and scientific articles and, has undergone testing both previously and currently, making it potentially usable in practice, particularly in autonomous driving. This dataset was established in 2011 in Germany at Ruhr University Bochum. In this study, we divided the dataset into two groups: the first group, representing 80 % of the training data, and the second group, representing 20 %, for testing. Note that the distribution of categories within it is unbalanced due to weather conditions. This dataset has unique features, including the following:

- The images in the German traffic signal dataset are diverse, and many were captured in a variety of weather conditions. This, in turn, creates challenges for researchers in finding appropriate solutions.
- Wide distribution of categories: It includes 43 categories covering most types of regulatory, warning, and advisory traffic signs approved in the German system.
- Variation in signal size and resolution: Signal sizes vary between images, which tests the models' ability to recognize patterns regardless of size or dimension.
- It is also characterized by being normalizable and modifiable, which allows deep learning models to handle it easily.
- The data are divided into two groups: 80% for training and 20% for testing, resulting in the following percentages: 39,209 for training and 12,630 for testing. Sometimes, it is divided into three groups: training, verification, and testing.

In the German traffic sign dataset. We observe various types of these categories, as shown in Figure 2. These categories include children's crossing and "no entry" signs. Other categories include uneven roads, right and left turns, yielding, and bus stops. Other categories include the end of all restrictions, animal crossing warnings, and caution against ice. and others that specify speed limits, for example, 80 and 100 km/h. From all of this, it becomes clear that there is diversity in these categories. This allows us to conduct a classification process that is realistic and practical. so that it can be used in intelligent transportation systems and autonomous driving.

Figure 2: Different samples of the GTSRB data set

3.2 DATA PREPROCESSING

All images underwent a set of standardized pre-processing steps before being fed into neural networks models., These steps first involved resizing the images to a fixed dimension of 224×224 pixels to ensure compatibility with the requirements of the pre-trained deep models., The images were then converted into numerical representations (Tensors) suitable for the PyTorch environment, which allowed them to be handled efficiently during training and extraction processes. The Normalization process was also applied using the mean and standard deviation of the ImageNet dataset, which helped to standardize the color distribution and reduce the differences between images., No data augmentation techniques were used because the GTSRB database was rich enough in terms of sample size and diversity of imaging conditions, including differences in lighting, shooting angles, and degrees of noise, which enhanced the models' ability to generalize without the need for artificial increases in data.

3.3 PRE-TRAINED CNN MODELS AND MLP CLASSIFIER

This research relied on a set of pre-trained convolutional neural networks including GoogleNet, VGG19, resnet18, EfficientNet-B1, MobileNetV2, ResNet50, and Densenet121, to benefit from their different capabilities in extracting high-level representative features from images, Each model has been modified by removing the Fully Connected Layer so that the deep outputs are used as distinct representations of traffic signal characteristics, The diversity of these models in terms of depth, number of parameters, and network structure allowed for the extraction of rich and broad features that contribute to enhancing the overall performance of the classification process.

After obtaining the extracted features, a unified multi-layer classifier (MLP) was designed for all models, where the value of input-dim was adjusted according to the size of the extracted features from each network, The classifier consists of an input layer followed by a hidden layer that includes (512) neural units with Batch normalization and ReLU as an activation function, in addition to a dropout layer (0.3) to reduce the possibility of overfitting, The output layer consists of (43) units representing the number of traffic signal categories in the database, The classifier was trained using the Adam algorithm with (weight decay) and StepLR learning scheduling, which allowed for a balance between convergence speed and quality of results. Table 2 shows the hyperparameters of the multi-layer classifier MLP used in this research, including the internal structure and training mechanism.

Table 2 :Hyperparameters of the proposed multilayer classifier

Hyperparameter	Configuration
Learning rate	0.001
Batch Size	64
Epochs	100
Dropout ratio	0.3
Size of hidden layers	512
Activation function	ReLU
Optimizer	Adam

3.3 PROPOSED DENSENET121- MLP INTEGRATED FRAMEWORK

The proposed model is based on combining the power of the DenseNet121 model in extracting deep features with the efficiency of a multi-layer classifier (MLP) in performing final classification with high accuracy. The primary goal of building this proposed model is to construct a system capable of handling visual samples of traffic signals, as well as dealing with the conditions under which those images were captured, from noise to other conditions. The implementation mechanism begins by extracting high-resolution features using the DenseNet121 model. In this case, convolutional layers and blocks are preserved because they maintain high-resolution features. The proposed model structure consists of four dense blocks. separated by transition layers that maintain the sequential and regular transmission of information.

These blocks contain units, and each unit consists of a three-part sequence including ReLU bundles in addition to (3*3) convolutional layers. In this case, the output from each unit is passed to the units immediately following it. This rich interconnectedness enables the utilization of the acquired features in the completed phases. Therefore, our system generates rich and stable features capable of capturing everything related to any category of traffic signals used. After completing the detour stages. Then, a layer is employed. Global average (To extract the final features, which consist of 1024 elements, representing the pivotal and profound characteristics of each of its images. This implementation phase is very important in reducing the number of parameters while preserving visual details. This results in highly accurate and classifiable data.

In the next step, the characteristics and features move to the MLP classification. stage to achieve a balance between efficiency and high accuracy. The multilayer classifier consists of a light layer of up to (512) knots. It is equipped with batch normalization and a ReLU function in addition to a dropout rate of up to (0.3). Its benefit lies in reducing overlearning. The final stage contains 43 nodes.

Representing traffic signals, which represent the categories specific to this data set used in our scientific research. We used the algorithm known as Adam because, of its advantages, firstly, in reducing fluctuations in weight updates, and secondly, its speed in learning. StepLR was also used because it helps regulate the learning rate and improves training courses. Cross-entropy loss was also employed and performed a diverse and multicategory classification process.

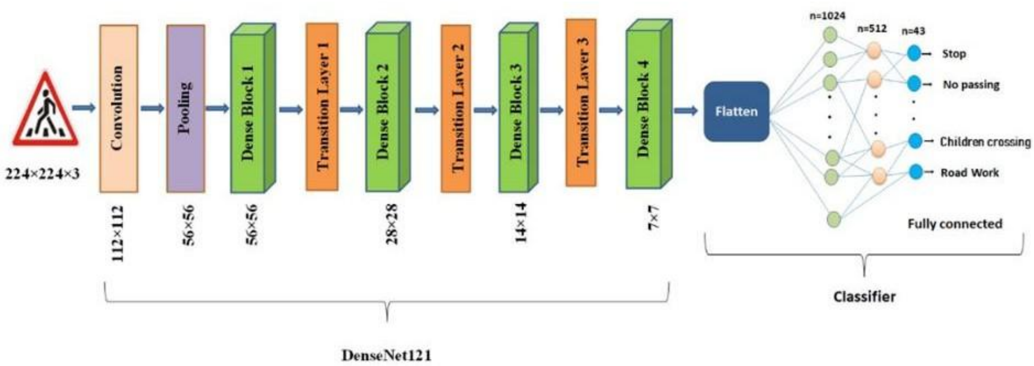


Figure 3: Architectural design of the proposed model (DenseNet121).

The design of the proposed model used in our scientific paper (Densenet121). Its high-resolution feature extraction and the use of MLP in the classification process have a positive impact on achieving a balance between model efficiency and high accuracy. The DenseNet121 model's dense structure optimizes information as it is passed between layers. thus preventing the loss of extracted features during forward propagation. This results in rich, accurate, and in-depth features. On the contrary, MLP employs a method of using enhanced features and representations to make appropriate and highly accurate classification decisions. This allows the proposed structural model to be sound and feasible in practice. especially in autonomous driving systems. Figure 3 presents the proposed methodological framework. This model consists of two parts: the first is DenseNet121 and, the second part is MLP. is used to perform the classification of categories. The design of the model consists of several stages. Initially, raw images taken from the dataset used in our research paper are imported. These images are then transferred through dense blocks, followed by a stage called flattening, which feeds the multi-layer classifier. The combination of the model used, which achieved the highest accuracy among the seven models used in our research, and the use of a multi-layer classifier. allows the proposed structural model to strike a balance between speed in execution and the quality of features and representations. This enables its practical application, especially in transportation and autonomous driving systems.

3.4 EVALUATION METRICS

The methodological framework of this research Work was evaluated on four accuracy criteria, which are as follows:

Accuracy: This standard unit is measures the accuracy of the model used relative to the number of positives that have been correctly identified.in other words, it measures how many predictions are correct relative to the remaining predictions [24].

$$\text{accuracy} = \frac{TP + TN}{TP + TN + Fp + FN} \quad (1)$$

precision: This criterion is defined as the ratio of all classifications correctly categorized by the model to actual positive classifications [24].

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

recall: This criterion can be defined as the ability of the model to detect all positive samples from among all positive samples existing [24]

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

F1-score: This scale is also known as the criterion for achieving a balance between the recall scale and the precision scale, and its law is as follows [24].

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

4. EXPERIMENT AND RESULTS

In this section of our research paper, we seek to clarify and explain what was done to the German traffic sign dataset. highlighting the most significant results and practical experiments conducted using the proposed model framework and,how to use the multi-layer classifier. Following this, we compare our findings with those of prior research. We also explain the equipment used in our research work, where a laptop (HP Elite Book) was used, containing a Core i7 processor and 16 GB of RAM, with Windows (10 operating system). From a programming perspective, we used Python version (3.8). Within the Spyder interface. Note that this version is capable of executing all libraries used in this language and contains a few errors during execution. As for the libraries used, we only used the most prominent and well-known libraries for the Python language, especially those used in deep learning, which are as follows: (Matplotlib), (PyTorch), (NumPy), in addition to using (h5py) and other libraries as well. The equipment used, both hardware and software-related, and all the tools employed, contributed to the accurate and highly efficient execution of the model. Table 3 presents the most important results obtained regarding the criteria used for accuracy, including accuracy, precision, recall, and F1-score. The seven models used in this work are DenseNet121, VGG19, MobilenetV2, ResNet-18, ResNet50, and GoogleNet EfficientNet-B1. These are all deep learning models, and the features and representations were extracted using them. These results were obtained by combining the extracted features with a multi-layer classifier.

Table 3: Performance of pretrained-models with multilayer perceptron

Model (%)	Accuracy (%)	Precision (%)	Recall (%)	F1(%)
GoogleNet	97.95	98.18	97.64	97.90
VGG19	98.32	98.49	98.40	98.44
ResNet18	98.65	98.90	98.55	98.72
EfficientNet-B1	99.07	99.39	99.20	99.29
MobileNetV2	99.15	99.46	99.29	99.37
ResNet50	99.22	99.40	99.20	99.30
DenseNet121	99.41	99.53	99.44	99.49

The results show that DenseNet121 achieved the highest accuracy of 99.41%, outperforming the rest of the models, while ResNet50 and MobileNetV2 achieved similar performance with an accuracy of 99.22% and 99.15%, respectively. As for lighter models, such as Google Net, they recorded a lower accuracy of 97.95%, which reflects the variation between the depth of the network and the number of its parameters on the one hand and, its ability to extract representative features on the other. These results show that increasing the depth and complexity of some models, such as DenseNet121, contributes to improving the quality of the extracted features, while lighter models, such as MobileNetV2, maintain the advantages of computational efficiency despite a slight decrease in performance. Figures (4) and (5) show the loss and accuracy curves for the Google Net and VGG19 models, respectively, where the gradual decrease in loss is evident in parallel with the continuous increase in accuracy until reaching the stability stage after a limited number of training epochs. Similarly, Figures (6), (7), and (8) show the performance of ResNet18, EfficientNet-B1, and MobileNetV2, where the models show remarkable generalization ability with slight variation in convergence speed and quality of final results. Figures (9) and (10) show the training curves of the ResNet50 and DenseNet121 models, which showed outstanding performance in terms of loss stability and high levels of accuracy.

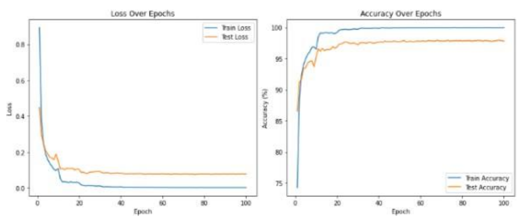


Figure-(4): Google Net accuracy and loss curve

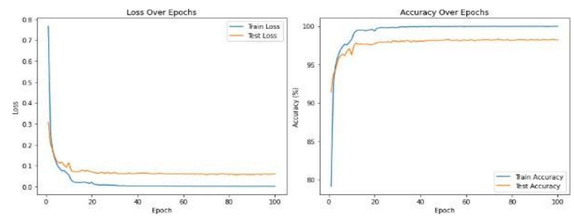
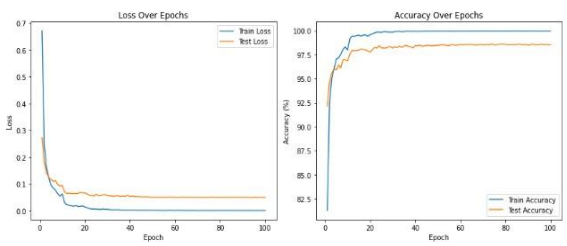
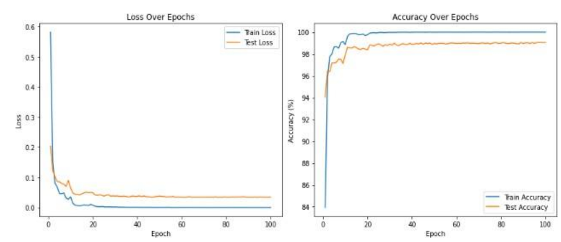


Figure (5): VGG19 accuracy and loss curve



Figure(6): Resnet18accuracy and loss curve



Figure(7): EfficientNet-B1 accuracy and loss curve

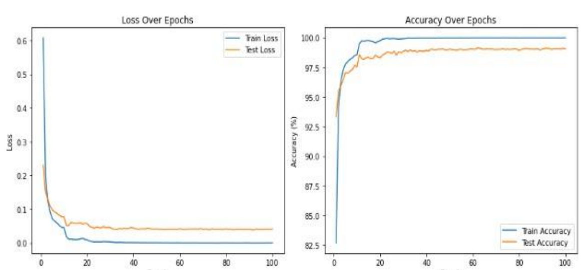


Figure (8): MobileNetV2 accuracy and loss curve

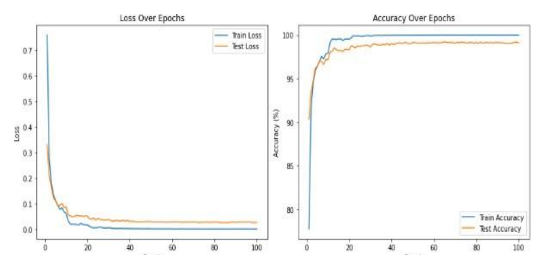


Figure (9): ResNet50 accuracy and loss curve

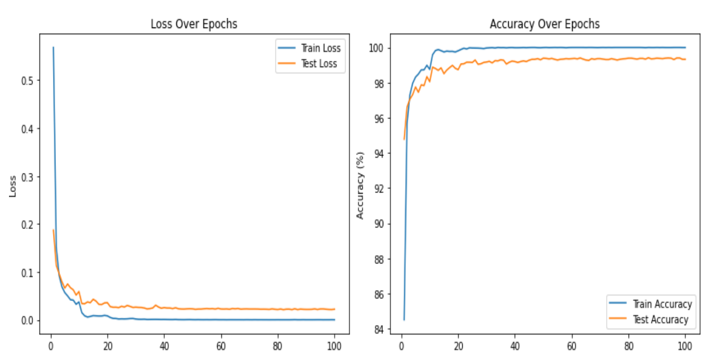


Figure (10): DenseNet121 accuracy and loss curve

After analyzing the results of the proposed models and clarifying their performance across the four metrics, it becomes necessary to compare them with the most prominent previous studies in the field of traffic sign recognition to evaluate the position of this research within the general framework of published works and to verify the extent of its superiority or convergence with the latest findings of studies., Table 4 shows a comparison of the performance of the proposed model (DenseNet121 + MLP) with the most prominent previous studies [1-21] that dealt with traffic sign recognition.

Table (4): Comparison of the performance of the proposed model with previous works

Reference	year	Model	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
D.Williams [23]	2024	CNN	0.86	-	0.85	0.86
H.Fu and H. Wang [12]	2021	ConvNet	90.13	-	-	-
L.VIEIRA [20]	2024	YUV-HOG	91.25	91.62	87.65	89.08
S. Jonah and S. Orike [11]	2021	8-Layer CNN Model	96	-	-	-
T. Lin [26]	2025	ResNet-18	96.19	-	-	-
Y.An et al.[21]	2024	Optimized LeNet-5network	97.53	-	-	-
C. Mai [27]	2025	CSO – AGA Hybrid Algorithm	97.97	-	-	-
A.A. Sikander and H. Ali [14]	2021	LeNet-5	98	-	-	-
L.W. Sheng et al.[13]	2021	VGG16 + VGG19 + Random Forest	98.38	98	98	98
S.Mingwin et al.[22]	2024	EATFormer	98.41	98.51	98.41	98.42
M.A. Khan et al.[18]	2023	Lightweight Neural Network	98.41	98.51	98.41	98.42
X. R. Lim et al.[17]	2023	Ensemble learning	98.84	98.84	98.84	98.84
M.A. Khan and H. Park [24]	2024	CNN	98.85	98.91	98.85	98.84
proposed	2026	DenseNet121	99.41	99.53	99.44	99.49

The experimental results showed that the proposed methodology achieved a high accuracy of 99.41%, outperforming many previous studies that relied either on a single neural network architecture or on traditional classification algorithms., This superiority is due to combining the power of pre-trained deep models that provide rich representations of visual features with a unified multi-layer perceptron (MLP) classifier capable of efficiently integrating and processing these features., This integration has enabled the proposed model to achieve a remarkable balance between high accuracy and generalizability, which gives it a clear advantage over other methods that focus on only one dimension of the traffic sign recognition process.

5. LIMITATIONS AND FUTURE WORK

This work is based on practical experiments and results obtained with an accuracy of up to 99.41% using a set of German traffic signs. demonstrates that our research utilized only one set of traffic sign datasets. and did not employ another set to be more comprehensive. Moreover, relying on pre-trained deep models requires relatively high computational resources, which may limit the possibility of practical application in systems with limited capacity, such as embedded devices or real-time applications. Regarding future work, it is possible to expand the study to include additional databases, such as (BTSD) or (TSRD), to enhance generalizability. (Augmentation)techniques can also be combined to simulate more diverse imaging conditions to better reflect real-life environments. Another promising direction is to explore more efficient models, such as vision transformers or tiny ML models, that can be deployed on low-power hardware. In addition, the interpretability of the model can be studied through (XAI) (Explainable AI) techniques to enhance transparency and support decision-making in autonomous driving systems.

6. CONCLUSIONS

This paper presents an integrated methodological framework for traffic sign recognition based on the GTSRB database by employing pre-trained deep models, including Google Net, VGG19, ResNet18, EfficientNet-B1, MobileNetV2, ResNet50, and DenseNet121, to extract distinctive features and combine them with a unified multi-layer classifier MLP to achieve high accuracy and reliability in classification. The results showed that the proposed approach achieved an accuracy of 99.41% using the DenseNet121 model as the best feature extraction architecture, outperforming many previous studies that relied on a single architecture or traditional methods. We observe that using more than one type of convolutional neural network (CNN) leads to obtaining many of the specific properties of these models. This helps the multi-layer classifier (MLP) used with all the models to increase its generalizability and its application in intelligent transportation systems. When comparing our research with other studies, we compared, we observed that our proposed methodology achieves a balance between efficiency and accuracy.

This generates a superior model in both the acquisition of features and optimal classification achieved through outstanding performance. The main contribution of this study is the possibility of extracting these representative features from pre-trained models. Then, using (MLP) can use these features to obtain high accuracy. so that this methodological framework k can be used in practice and developed further at a later time. Another contribution of this research is that we used four metrics to measure accuracy, which is important to determine the efficiency of the model used. Through our work, which has encompassed almost all types of previous studies, and through experiments and conclusions, we observe that this work can represent an advancement in this field and can be further developed for future practical application.

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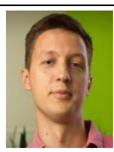	Loshkarev Ilya V. Associate professor at Institute for Mathematics, Mechanics, and Computer Science in the name of I.I. Vorovich, Russia:iloshkaryov@sfedu.ru
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