HyperEstimator: Evolving Computationally Efficient CNN Models with Grammatical Evolution

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Abstract: Deep learning (DL) networks have the dual benefits due to over parameterization and regularization rendering them more accurate than conventional Machine Learning (ML) models. However, they consume massive amounts of resources in training and thus are computationally expensive. A single experimental run consumes a lot of computational resources, in such a way that it could cost millions of dollars thereby dramatically leading to massive project costs. Some of the factors for vast expenses for DL models can be attributed to the computational costs incurred during training, massive storage requirements, along with specialized hardware such as Graphical Processing Unit (GPUs). This research seeks to address some of the challenges mentioned above. Our approach, *HyperEstimator*, estimates the optimal values of hyperparameters for a given Convolutional Neural Networks (CNN) model and dataset using a suite of Machine Learning algorithms. Our approach consists of three stages: (i) obtaining candidate values for hyperparameters with Grammatical Evolution; (ii) prediction of optimal values of hyperparameters with supervised ML techniques; (iii) training CNN model for object detection. As a case study, the CNN models are validated by using a real-time video dataset representing road traffic captured in some Indian cities. The results are also compared against CIFAR10 and CIFAR100 benchmark datasets.

1 INTRODUCTION

Deep learning has started to gain dominance since early 2000 and is now being used in prominent industrial applications such as, language translations, gaming, analysing medical scans, prediction of protein folds to name a few. Convolutional Neural Networks (CNN) is a powerful approach to solve image analysis tasks. However, it is not trivial finding the optimal architecture from the huge search space of all possible architectures for the given task. CNN model consists of various elements, layers and hyperparameters, leading to a huge number of possible CNN architectural designs. As a result, a lot of time is invested on determining the optimal structure based on multiple manual experiments. With the exponentially increasing amounts of data, much research has been done in this area and numerous architectures have been constructed, such as LeNet (Lecun et al., 1998), AlexNet (Krizhevsky, 2009), VGG (Simonyan and Zisserman, 2014), ResNet (He et al., 2015), and Google Net (Szegedy et al., 2014). One of the well-known issues about CNN is choosing optimal hyperparameters for academic or toy benchmarks and even more difficult on real-world scenarios. There is no definitive answer as to which activation function to choose, which optimizer or learning rate suits the best for all datasets. Moreover, deep learning networks have millions of parameters and if they are trained with flexible computer models then such learnings can lead to universal approximations, meaning that the values can fit any type of data. This is the emerging research direction with the introduction of data-centric AI (Ng, 2021b) which has given rise to the research for finding optimal settings of hyperparameters or the CNN architectures. Data-centric AI approaches the field of solving AI problems with a data driven approach. In other

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words, instead of investing in high-end computational resources for finding an appropriate AI model for a given dataset, the focus is shifted to finding appropriate data for the model. The other paradigm of data-centric AI focuses on shifting from big data to good quality data for training the AI models (Ng, 2022). AI model training can start on small datasets which can subsequently be scaled to big data. These approaches are beneficial when dealing with small amounts of data as is the case in the healthcare domain. Moreover, collecting and processing big data is an expensive activity. Hence, collecting unbiased (from human interventions), valid and good training data samples is an interest to the researchers (Ng, 2021a). The AI models that are characterized by the following properties are able to achieve the targets of data-centric AI:

- It should use limited *computational power*;
- It should be trained efficiently on *smaller amount of data*;
- It should be flexible enough to adapt to *varying data instances*;
- It should be *interpretable and explainable*.

If all of the above characteristics are satisfied, the AI model could lead to huge savings in revenues thereby reducing the overall project cost in terms of computational resources and efforts. The aim of this research work is to achieve the above defined characteristics for AI models, with a specific focus on obtaining optimal CNN architectures. In particular, the objective is to tune the hyperparameters of state-of-the-art CNN model with our approach.

2 BACKGROUND STUDY

The design of CNN is based on the visual perception of living beings (Ghosh et al., 2020). The model's learning ability is attributed to the utilization of many features extraction stages that can automatically learn patterns from data. The performance of a CNN is not only affected by layer design but also by other hyperparameters such as activation function, normalization method, loss function, regularization, optimization, learning rate, etc. One of the most difficult aspects of using CNN-based approaches is determining the best hyperparameters to use.

The authors in (Bochinski et al., 2017) argue that there seem to be no reliable ways to identify certain network architectures that could contribute to big performance gains. The techniques based on experience yields typically conventional hyperparameters rather than optimal ones (Yu and Zhu, 2020). The problem with the brute force techniques results in massive hyperparameter combinations leading to computational overheads. Hence, there is a need to automate the process of finding the optimal hyperparameters. According to (Andonie and Florea, 2020), Grid Search, Random Search (RS), Bayesian Optimization (BO), Nelder- Mead, Simulated Annealing, Particle Swarm Optimization, and Evolutionary Algorithms are the most well-known methods for finding optimal hyperparameters.

Evolutionary algorithms combine the ideas of RS and BO, where each possible solution reflects a point in the hyperparameter space. This technique is particularly suited for optimization problems over high-dimensional variable spaces, because maintaining several individuals, i.e., potential solutions, resulting in exploring several solutions in parallel. A number of studies have proposed different techniques using evolutionary algorithms, especially GE, to design and optimize neural networks. For example, (Tsoulos et al., 2008) present a grammar to build and train a neural network using GE. The grammar proposed specifies the topology of the network, as well as the parameters weights, inputs and bias. This research only evolved two-layer networks, which were tested on classification and regression problems.

(Ahmadizar et al., 2015) described an approach that combines genetic algorithm (GA) and grammatical evolution. Specifically, GE is used to represent the network topology, while GA encodes the connection weight. Similar to the study of (Tsoulos et al., 2008), this method also creates a feedforward artificial neural network with only one hidden layer.

Another interesting approach is proposes by (Stanley and Miikkulainen, 2002) called NEAT (NeuroEvolution of Augmenting Topology) to evolve the structure of a neural network with its weights. NEAT has proven to be successful in generating structure and weights of relatively small recurrent networks (Miikkulainen et al., 2017). An Extension to NEAT is DeepNEAT, which is a method to evolve network topology and hyperparameters of deep neural networks. However, the resulting networks are frequently complex and unprincipled. Consequently, (Miikkulainen et al., 2017) improved this method and created the variant called CoDeepNEAT. CoDeepNEAT includes evolving two separate populations, one for the modules and one for the blueprints, based on the concept used in DeepNEAT. In contrast to DeepNEAT, CoDeepNEAT is capable of exploring more diverse and deeper architectures. However, the downside of CoDeepNEAT is the huge demand of computational resources (Miikkulainen et al., 2017).

In 2018, (Assunção et al., 2018) introduced

DENSER, which is a method for evolving deep neural networks. It combines GA and GE in order to evolve sequences of layers and their parameters. The parameters are encapsulated in a position of the GA genotype, which makes the use of genetic operators easier. In their study, they applied this approach to CNNs with remarkable results. In fact, it outperforms previous state-of-the-art evolutionary concepts to generate CNNs, such as CoDeepNEAT, in terms of accuracy. However, DENSER does not include optimization layers such as the dropout layer (Assunção et al., 2018).

(Baldominos et al., 2018) used GE in order to generate the optimal topology of a CNN along with many of its hyperparameters. Since the computational complexity of training and evaluating a CNN model is very high, a proxy was utilized to estimate the CNN performance. In particular, the fitness of the CNN models, which was the F1-score, were evaluated on drastically reduced number of epochs and training samples. As a result, the improved CNN model outperformed earlier state-of-the-art findings, which inspired us to design a data-driven approach.

We try to address the targets of data-centric AI as explained in Section 1 - finding optimal hyperparameters for an AI model using *minimal data* and *computational power*, while also focusing on the *explainability* and *interpretability* of its predictions.

3 PROPOSED SYSTEM

In this research work, we propose a system named as *HyperEstimator* that estimates - for a given CNN architecture - the optimal hyperparameters, from the given search space of their configurations. The pipeline of the proposed system is as illustrated in Figure 1. *HyperEstimator* comprises a suite of Machine Learning (ML) techniques, viz. GE, Linear Regression and Bayesian Optimser which sequentially estimate the optimal hyperparameter configurations. GE exploits the global search space and finds the possible candidates for the optimal configurations. These are then fed to the Linear Regression and Bayesian Estimator models which exploit the local search space and results in the possible best optimal configuration for the hyperparameters.

Mathematically, we can say F is a function of *HyperEstimator* that finds the optimal hyperparameters $H_1, H_2, H_3, \ldots, H_n$. As this is a challenging task to estimate hyperparameters for a given CNN architecture, the function F is learnt by the model using Bayesian Estimator s parameterised with weights w. So, we can define F as, $s = F(\sum_{i=1}^{n} H_i w_i)$. The function s estimates the optimal values of $H_1, H_2, H_3, \ldots, H_n$.

The weights are fed to the Bayesian model, s by learning the weights $w_1, w_2, w_3, \ldots, w_n$ and intercept α with regressor function r. Hence, the function s can now be defined as in Equation (1).

$$s = r(F(\sum_{i=1}^{n} H_i w_i), \alpha) \tag{1}$$

where α is the intercept of the regression model, r.

The metadata for the linear regression model, which provides information about the important features for predicting the accuracy, is generated by the GE framework. When the population in GE starts evolving, the phenotypes of the individuals I over the population size p, and their fitness values V over the last generation g are collected and fed to the regressor model. Mathematically, the GE model h can be represented as in Equation (2).

$$h = \{(I_{pg} V_{pg}) | p \in 1, 2, \ldots popsize, \ g \in 0, 1..gensize\} \tag{2}$$

Hence, in summary, the mathematical model of HyperEstimator can be represented as follows

$$s = r(F(\sum i = 1^n H_i w_i), \alpha)$$

where the input instances to the regressor model, r are given follows:

$$h = \{(I_{pg} V_{pg}) | p \in 1, 2, \ldots popsize, \ g \in 0, 1..gensize\}$$

3.1 Automatic Exploration of Hyperparameter Space with GE

Algorithm 1 defines automatic exploration of hyperparameter space with GE. *HyperEstimator* approaches the tuning of hyperparameters in a data-driven way. Hence, *HyperEstimator* tries to determine the optimal hyperparameter configurations by testing the feasibility of using minimal data for tuning the hyperparameters. However, we also make sure that we are providing a balanced dataset capturing all the real-world instances of the image dataset. In the process of tuning hyperparameters, we start the preliminary studies by creating a custom dataset for vehicle detection in road traffic. We collect images from multiple sources and capture to the best of our knowledge, all the real-world instances of the vehicle classes. We then take a sample of 5% of the training dataset in the first phase for obtaining the values of the hyperparameters. (Baldominos et al., 2018) also shows that this strategy works while tuning hyperparameters if we have a balanced dataset.

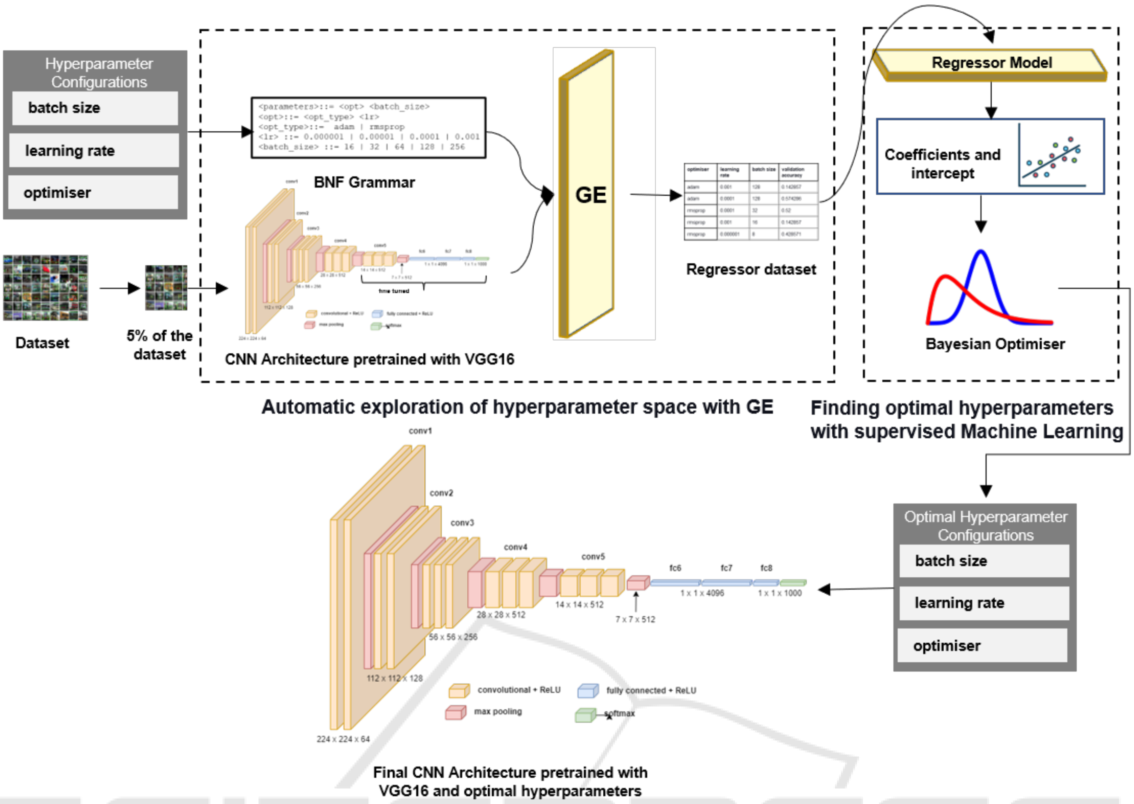


Figure 1: Pipeline of the *HyperEstimator* Model.

GE (Ryan, 2010; O'Neill and Ryan, 2001; Ryan et al., 2018) is an evolutionary algorithm that evolves a solution from the search space for a given problem with the evolutionary strategies. The key functionality of genotype to phenotype mapping with Backus-Naur Form (BNF) (Ryan, 2010) grammar in GE generates syntactically correct phenotypes, and makes it programming language independent and hence, useful across multiple problem domains. In the proposed system, the search space of hyperparameter configuration of the CNN model is converted to BNF grammar. The CNN architecture is then evolved using 5% of the training dataset. The phenotypes of the population in the search space of GE and their fitness scores (Lima et al., 1996) are collected for the last generation, in our case, the 5^{th} generation, in a separate file to feed to the regressor model.

Algorithm 1: Automatic exploration of hyperparameter space with Grammatical Evolution.

Input: BNF Grammar, CNN architecture, 5% of the image dataset, generation size *gen size*, population size *pop size*
Output: Dataset of phenotypes of the individuals and their fitness

for $g = 1$ to *gen size* **do**
  for $p = 1$ to *pop size* **do**
    I_{gp} = Phenotype of the individual from the BNF Grammar
    V_{gp} = Fitness of the individual I_{gp}
  end for
  if g is equal to the last generation **then**
    Add I_{gp} and V_{gp} to the *individuals.csv* file
  end if
end for

3.2 Finding Optimal Hyperparameters with Supervised Machine Learning

A linear regressor model is a ML technique that extracts the relationship between one or more explanatory variable and the target variable (Bindra et al., 2021). The dependent variables are hyperparameters $\{H_1, H_2, H_3 \ldots, H_n\}$ and the predictor variable is the *validation accuracy*. The regressor model performs the feature extraction and predicts the weights for each of the hyperparameter configurations and the intercept, by minimising the regression loss as defined in Algorithm 2.

The Bayesian Optimiser (Bindra et al., 2021), which is based on the maximum likelihood function, then uses this regression model to predict the optimal

Algorithm 2: Finding optimal hyperparameters with supervised Machine Learning - **Regressor Model**.

Input: Individuals from *individuals.csv* file returned by GE
Output: Weights $\{w_1, w_2, ...w_n\}$ and intercept α
1: **while** w_i not converged **do**
2: Initialise the weights $\{w_1, w_2, ...w_n\}$ and intercept α with random values
3: $validation\ accuracy_{predicted} = \alpha + H_1 w_1 + H_2 w_2 + ... + H_n w_n$
4: $error = \sum_{i=1}^{instances}(validation\ accuracy_{actual} - validation\ accuracy_{predicted})^2$
5: Update weights $\{w_1, w_2, ...w_n\}$ and intercept α to minimize error
6: **end while**

hyperparameters for the CNN model as defined in Algorithm 3. The Bayesian Optimiser maximises the *validation accuracy* (objective function). The CNN model is then trained on the entire dataset with the optimal hyperparameters obtained from the *HyperEstimator*.

Algorithm 3: Finding optimal hyperparameters with supervised Machine Learning - **Bayesian Estimator**.

Input: Hyperparameter space D, number of iterations n, target objective function $validation\ accuracy = \alpha + H_1 w_1 + H_2 w_2 + ... + H_n w_n$
Output: Optimal hyperparameter configuration $HC = \{H_1, H_2, H_3 ..., H_n\}$
1: Set initial hyperparameter configuration $HC = \{H_1, H_2, H_3 ..., H_n\}$
2: Evaluate the objective function $validation\ accuracy$
3: **while** $i < n$ **do**
4: Select new hyperparameter configuration HC_{n+1} by optimizing the acquisition function a: $HC_{n+1} = HC\ a(HC, D)$
5: Evaluate the objective function $validation\ accuracy_{n+1}$
6: Augment $D_{n+1} = \{D_n, (HC_{n+1}, validation\ accuracy_{n+1})\}$
7: Update model
8: **end while**

3.3 *HyperEstimator* Computational Complexity

The computational complexity of our approach can be seen as a combination of the complexity of all ML techniques used in the pipeline. Hence, we can define the complexity of the *HyperEstimator* as in Equation (3).

$$O(HyperEstimator) = O(GE) + O(LR) + O(BO) \tag{3}$$

where $O(GE)$ is the computational complexity of the GE model, $O(LR)$ is the computational complexity of the linear regressor and $O(BO)$ is the computational complexity of the Bayesian Optimizer. The computational complexity for Bayesian Optimization is known to be $O(x^3)$ (Lan et al., 2022), where x is the total number of candidate solution evaluations. The computational complexity for the linear regression model is $O(k^2(n+k))$, where n is the number of observation and k is the number of weights (Banerjee, 2020). GE is an evolutionary approach driven by an evolutionary search engine. In this research work, we have used GE driven by Genetic Algorithms (GA). Hence, computational complexity for GE is the complexity for GA and GE. The complexity for GA is defined as computational efforts for the evaluation of the individuals. This leads to an overall complexity of GE as the product of complexity fitness function and the number of fitness evaluations.

$$O(GE) = O(fitness\ function) * (\#fitness\ evaluations) \tag{4}$$

The computational efforts of the fitness evaluations are determined by the population size, size of each individual and number of generations, and the genetic parameters used such as crossover and mutation. However, according to (Oliveto and Witt, 2015), as the time for genetic parameters applied is same for each individual, we do not consider it in the computational efforts and it is considered as $O(1)$. Hence, the number of fitness evaluations can be calculated as $\#of\ fitness\ evaluations = (population\ size)(size\ of\ individual)(\#of generations)$. The complexity of the fitness function in our case is the complexity of the CNN architecture. To determine it, the number of floating-point operations (FLOPs) (Molchanov et al., 2016) are assessed for each layer in the CNN model. Combining all these individual computational complexities, we get the overall complexity of our approach. Hence, the computational complexity is as defined in Equation (5).

$$O(HyperEstimator) = O(GE) + O(x^3) + O(k^2(n+k)) \tag{5}$$

Table 1: Dataset Details. S1: MIO-TCD, S2: TAU Vehicle, S3: DelftBikes, S4: PASCAL VOC 2012.

Class	**Data Source**				**Total**
	S1	**S2**	**S3**	**S4**	
bicycle	2284	1618	1098	-	5000
car	3000	2000	-	-	5000
motorcycle	1982	2986	-	32	5000
pedestrian	5000	-	-	-	5000
van	4000	1000	-	-	5000
background	5000	-	-	-	5000
truck	3000	2000	-	-	5000
Total					35000

4 EXPERIMENTAL SETUP

This section discusses the dataset details and experimental setup for our approach.

4.1 Dataset Details

The dataset we used in our experiments are a combination of several sources which include labelled vehicle images. We combined them and created a subset consisting only of different vehicle classes. The datasets involved in this process are:

- The MIOvision Traffic Camera Dataset (MIO-TCD) dataset, which was released as a part of challenge in CVPR 2017 (Luo et al., 2018)
- TAU Vehicle Type Recognition Competition dataset from Kaggle (tau, 2020)
- DelftBikes (Kayhan et al., 2021)
- PASCAL VOC 2012 dataset (Everingham et al.,)

The MIO-TCD contains 11 different classes of vehicles for image classification and object detection tasks while TAU Vehicle data contains 36,500 images for 17 different classes of vehicle. DelftBikes contains 10,000 bike images while PASCAL VOC contains 20 object categories. There was a couple of motivation behind combining these four datasets:

- To have a balanced dataset for each vehicle class and hence avoid the problem of bias.
- To have a sufficiently large dataset for training the CNN model to avoid problems related to overfitting.

In the real-time video captured in some Indian cities, we observe the following classes of vehicles: $\{$*background, bicycles, car, trucks, van, motorcycle, pedestrian*$\}$. As the objective of the experiments was to test the CNN model on the above real-time traffic videos, we selected only those classes as mentioned above from the MIO-TCD dataset. We have used 7 classes for training with 5000 images in each class. The distribution of images from each of the datasets into respective classes is shown in Table 1.

Figure 2: Sample images for each class from the image dataset with data augmentation techniques.

4.2 CNN Architecture

For the experiments, we used the VGG-16 model and incorporated transfer learning by using the pretrained weights from the Imagenet (Deng et al., 2009) dataset. The CNN architecture used was the same as that of the literature (Kshirsagar et al., 2022; Kshirsagar et al., 2021). Hence, we used the same CNN architecture for a fair comparison. We followed the process of freezing 70% of the layers while training only the remaining 30% of layers. The activation function used for the last layer was Softmax with 7 neurons, each representing a vehicle class and the image size, 224x224. The dataset was distributed into 80% for training and 20% for testing purposes. We augmented the image data by horizontal flip, vertical flip and rotating the images by 90° for robust training of the model. Figure 2 illustrates the samples of augmented images for each class of the dataset. The *steps per epoch* were calculated by dividing the number of training samples by the batch size while the *validation steps* were calculated by dividing the test samples by the batch size.

Table 2: Sample individuals obtained during evolutionary runs.

#	optimiser	learning rate	batch size	validation accuracy
1	adam	0.001	128	0.142857
2	adam	0.0001	128	0.574286
3	rmsprop	0.0001	32	0.52
4	rmsprop	0.001	16	0.142857
5	rmsprop	0.000001	8	0.428571

5 RESULTS

The hyperparameter space for the model consisted of $\{$*learning rate, batch size and optimiser*$\}$. The hyperparameter space was transformed into BNF grammar as shown in Figure 3 and fed to the GE model (Baldominos et al., 2018; de Lima et al., 2019).

```
<parameters> ::= <opt> <batch_size>
<opt> ::= <opt_type> <lr>
<opt_type> ::= adam | rmsprob
<lr> ::= 0.000001 | 0.00001 | 0.0001 | 0.001
<batch_size> ::= 16 | 32 | 64 | 128 | 256
```

Figure 3: BNF Grammar defining the hyperparameters of the CNN model.

A fitness function evaluates how well the individuals are performing in an evolutionary algorithm. In this research work, the evolved CNN models were evaluated by defining *validation accuracy* of the model as the fitness function with the goal of maximising it. The choice of values for each of the hyperparameters forms an individual or chromosome. e.g., one of the sample chromosomes from the BNF grammar can be *adam 0.0001 128*. Using the CNN architecture and 5% of the data from our dataset, we performed evolutionary runs with the BNF grammar for 5 epochs where the parameter setup was as follows: *population size: 10, generations: 5, tournament size: 2, elitism, initialization: sensible*. The experiments were performed using PonyGE2 (Fenton et al., 2017), the Python tool for GE using TensorFlow and keras library, and trained on Quadro RTX 8000 - Nvidia GPU. We stored all the candidate individuals from the 5^{th} generation in a *.csv* file to be used for the next step in our proposed pipeline. Sample values of the individuals generated during the evolutionary process are shown in Table 2.

The *.csv* file of the candidate solutions for the hyperparameter space was then fitted to a linear regression model to find the values of coefficients for the equation (6).

$$F = H_1 w_1 + H_2 w_2 + H_3 w_3 + \alpha \quad (6)$$

validation accuracy was the dependent variable while the independent variables were $\{$*optimiser, learning rate, batch size*$\}$. The Python library *statsmodels* (Seabold and Perktold, 2010) was used to fit the data into linear regression model. The values for $\{w_1, w_2, w_3\}$ and α obtained were as follows: $-3.18194782e-02, -3.80413117e+02, -3.09998001e-04$ and 0.6085946681414556 respectively. Replacing the values for the coefficients we get the following regression model as seen in equation (7).

$$\begin{aligned} F = (-3.18194782e^{-02}H_1) + (-3.80413117e^{+02}H_2) \\ +(-3.09998001e^{-04}H_3)+ \\ 0.6085946681414556 \end{aligned} \quad (7)$$

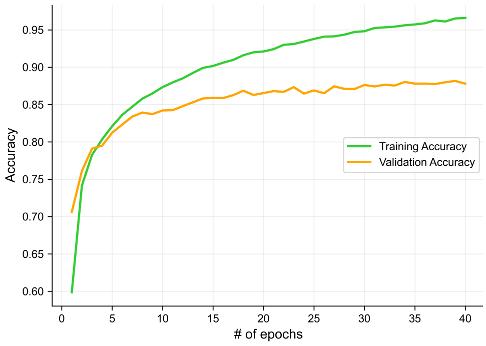
Maximum likelihood function was then used to get the best value of the hyperparameters for the CNN model with Bayesian Optimiser. The *hyperopt* (Bergstra et al., 2013) library was used to estimate the optimal values of hyperparameters. The *hyperopt* library contains a f_{min} function that minimizes the target. In our case, the target function was *validation accuracy* with an objective to maximise it, hence f_{min} was the reciprocal of *validation accuracy*. *hyperopt* contains a parameter, named as *max_evals*, that defines the number of configurations that the Bayesian Optimiser tries. This parameters is useful while tracking the subspaces of hyperparameters and their explainability. The following were found to be the best with Bayesian Optimiser: $\{$*H_1(optimizer): adam, H_2(learning rate): 0.000001, H_3(batch size): 16* $\}$.

The optimal hyperparameters obtained from our approach *HyperEstimator* were then used to train the CNN model on the entire dataset over 40 epochs, with an early stopping for the final model. The dataset was divided into 80% for training and 20% for validation. It took around 6 hours to train the CNN model with the optimal hyperparameters, achieving a validation accuracy score of 87%.

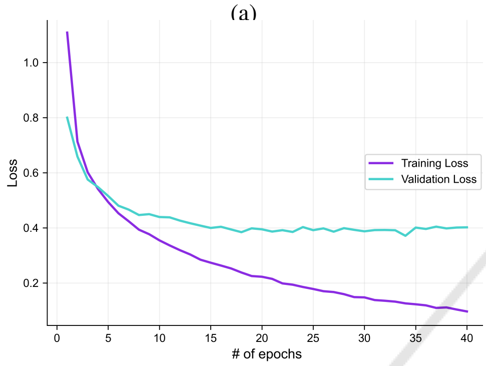
5.1 Comparative Analysis

In order to compare the results to those obtained in the literature, we also ran an experiment without the *HyperEstimator* approach using the hyperparameters as used in the literature (Kshirsagar et al., 2022). The CNN architecture was the same in both the approaches, only differing in the hyperparameters.

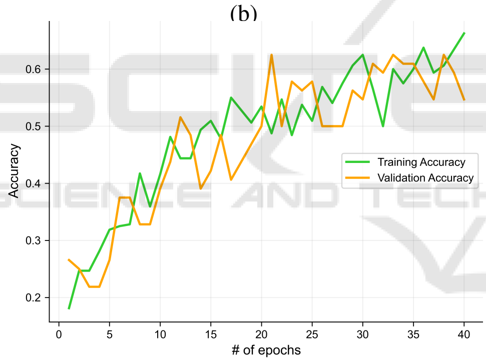
The performance of training and validation accuracies and losses across the epochs for both approaches are as illustrated in Figure 4. It can be observed from the graphs that there is a dramatic improvement in the validation accuracy when the model was trained with the hyperparameters tuned with *Hy-*



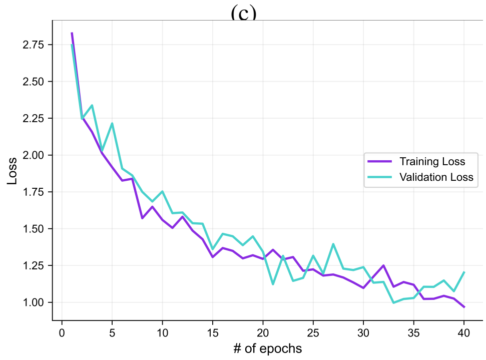
(a)



(b)



(c)



(d)

Figure 4: (a) Training and Validation accuracy and (b) Training and Validation loss for CNN models trained with hyperparameters with *HyperEstimator* (c) Training and Validation accuracy and (d) Training and Validation loss for CNN model trained with hyperparameters from (Kshirsagar et al., 2022).

Table 3: Qualitative analysis between models pre- and post-tuning with *HyperEstimator*. The pre-training model is referred from the literature (Kshirsagar et al., 2022). TA: Training Accuracy, TL: Training Loss, VA: Validation Accuracy, VL: Validation Loss. #1 Hyperparameters tuned without *HyperEstimator*, #2 Hyperparameters tuned with *HyperEstimator*.

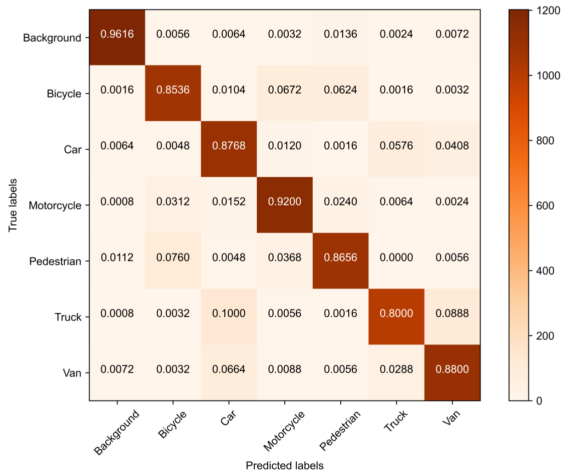
Approach	**TA**	**TL**	**VA**	**VL**	**Time (mins)**
#1	0.66	0.9	0.54	1.2	3 mins
#2	0.96	0.09	0.87	0.4	365 mins

perEstimator as compared to the model without using *HyperEstimator*. The validation accuracies for both the approaches are illustrated in Figure 4a and Figure 4c respectively. The validation accuracy achieved with the model tuned with *HyperEstimator* was 87% while that with without *HyperEstimator* was only 54%. We also observe a significant improvement in validation loss when the model was trained with the hyperparameters tuned with *HyperEstimator*, as shown in Figure 4b and Figure 4d. The comparative analysis of both the approaches in terms of accuracy and loss at 40^{th} epoch is presented in Table 3. As can be observed in column 4, the model's validation accuracy has improved significantly, though the time taken for the model training was competitively high.

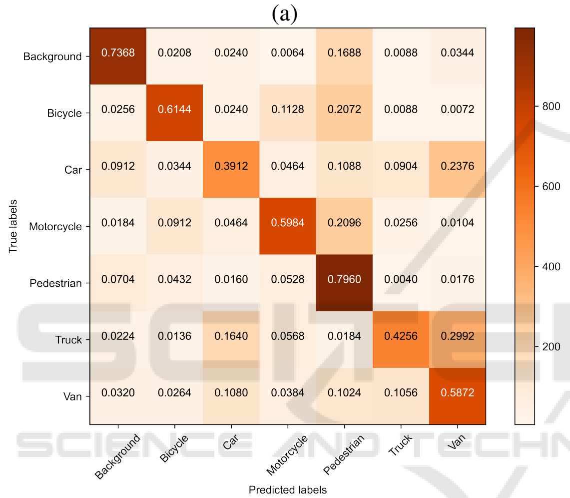
We also plotted the confusion matrix against the test data to understand how well the model performed for each class. Figure 5 shows the confusion matrix for both the approaches on the test dataset. All the classes were balanced and the accuracy has been normalized while plotting the confusion matrix; hence, each row will sum up to 1. In the plots, we can observe the CNN model tuned with *HyperEstimator* has learnt the major parameters for each class as compared to the traditional approach as illustrated in Figure 5a and Figure 5b. The model has achieved the maximum accuracy in classifying the *background* class with an accuracy of 96%. On the other hand, the model seems to misclassify the *bicycle* as *motorcycle* and *pedestrian* and vice versa. This may be due to the fact that the structures of *motorcycles* and *bicycles* are similar in a way and the images for pedestrian are blurred. This indicates the model still has scope to learn the features for these classes. Similar is the case with the classes, *truck* and *van*; the model misclassifies the truck with van and vice versa. This may be again due to the overlapping of the visual structures.

5.2 Model validation

The CNN model was tested against the real-world benchmark CIFAR10 (Krizhevsky, 2009) and CIFAR100 (Krizhevsky, 2009) datasets. CIFAR10



(a)



(b)

Figure 5: Confusion matrix plots for CNN model trained with 40 epochs and tested on test dataset with (a) Hyperparameters tuned with *HyperEstimator*; (b) Hyperparameters tuned without *HyperEstimator*.

Table 4: Comparative analysis of the CNN model tuned with *HyperEstimator* on real-world benchmark datasets.

Dataset	Classes	Accuracy
CIFAR10	Car	0.64
	Truck	0.57
CIFAR100	Bicycle	0.88
	Motorcycle	0.45
	Truck	0.71

dataset consists of a total of 60000 images across 10 classes, 5000 images per class for training and 1000 per class for testing. The size of the images is 32x32 in 3 color channels. CIFAR100 dataset consists of 60000 images across 100 classes, with 500 images per class for training and 100 per class for testing purposes. The images in CIFAR100 are of size 32x32 with 3 color channels. For CIFAR10, we had two similar classes in our dataset *car* and *truck* while for CIFAR100, we had three similar classes, *bicycle, motorcycle* and *truck*. While testing the images were upscaled to 224x224 as our CNN model had the input size of 224x224 and we tested the performance of our proposed model on these classes for CIFAR10 and CIFAR100 datasets. Table 4 shows the accuracy for each of the class against the CNN model evolved with *HyperEstimator*. From the tables we can infer that the model has good accuracy against real-world benchmark datasets.

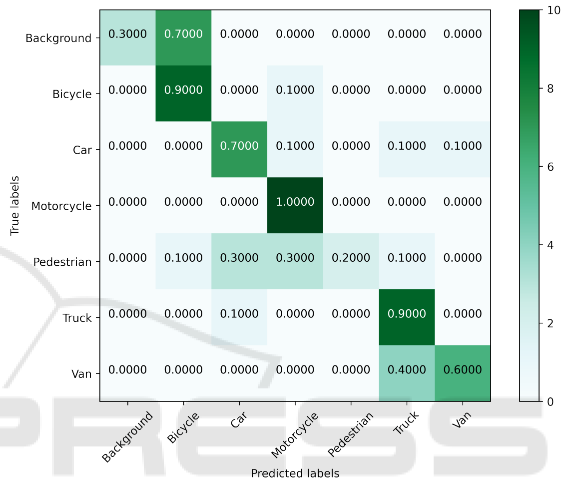


Figure 6: Confusion matrix plot for the CNN model tuned with *HyperEstimator* against real-world traffic video dataset.

5.3 Model Testing

To test the performance of the CNN model, we captured the real-time videos of the traffic in some Indian cities. We collected three videos of one minute each during daytime and at night. We divided the videos into frames and predicted the class obtained with the CNN model. We used 70 frames in total, 10 images per class for testing. The accuracy obtained was 0.65. Figure 7 illustrates the confusion matrix plot for the testing of the video dataset for each class. The results imply that the model tuned with *HyperEstimator* performs well in real-world scenarios for most of the class while there is still some scope for improvement against *background* and *pedestrian* class.

5.4 Interpretability of *HyperEstimator*

While using the trained AI models in real-world scenarios, it is critical to understand which parameters are important and how the model has learnt

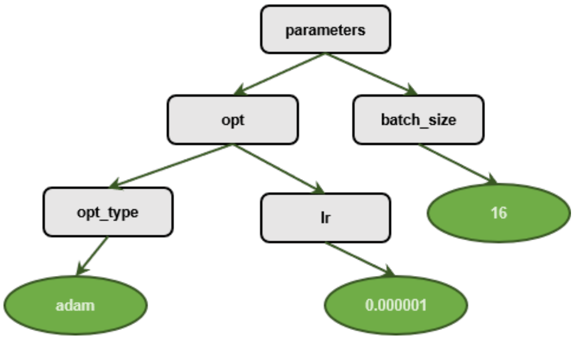


Figure 7: Example derivation tree from BNF grammar.

them for their trustworthiness. Explainable AI (XAI) (Holzinger, 2018) motivates the research for such models to explain their decisions. In this research work, *HyperEstimator* uses three key ML techniques all of which can be explainable for their results. GE uses genotype to phenotype mapping and generates a derivation tree for the individuals. This helps in understanding the solutions in human understandable form. The derivation tree in Figure 7 is obtained from BNF grammar, as shown in Figure 3. The *statsmodels* library from Python used for linear regression is interpretable. It displays all the metadata (statistical tests, confidence intervals, etc.) about the regression model in human understandable form. Similarly, Bayesian Optimiser is a probabilistic way of optimizing and incorporating explainability into the *HyperEstimator* system. In this research work, we have visualized the values of the features contributing to the target function in Bayesian Optimiser with *hyperopt* library. As explained in Section 5, *max_evals* determines the number of trials that the model uses to find the optimal hyperparameters. These trials can be visualised to analyse the contributions of each sub-space of the hyperparameters across the trials. Figure 8 illustrates the sub-spaces of hyperparameters in Bayesian Optimiser model. The figures clearly illustrate the major contributions of the optimal values across the trials. In this way, all the ML techniques of *HyperEstimator* system illustrate interpretability.

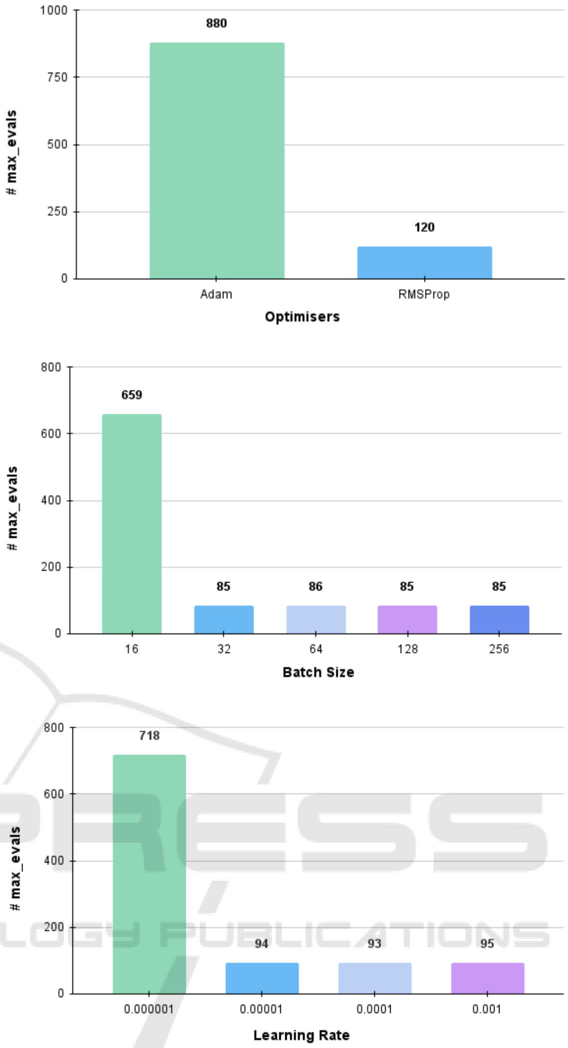


Figure 8: Feature subsets with their contribution in estimating optimal hyperparameters for Bayesian Optimiser.

6 CONCLUSIONS AND FUTURE SCOPE

In this research work, we propose *HyperEstimator*, a system consisting of a suite of ML techniques to reduce the computational efforts for tuning hyperparameters of CNN models. We employed GE for the hyperparameter search space whereas the Bayesian Optimiser exploited the local search space for the optimal values of hyperparameters. We present a case study on a real-world traffic image dataset and propose to use only 5% of the training data for hyperparameter tuning, to reduce the computational cost. With the obtained configurations for hyperparameters, we could significantly improve the validation accuracy to 87% for the CNN model. Initial results from our approach tested against the real-world benchmark datasets, CIFAR10 with two overlapping classes, viz. car and trucks, and CIFAR100 with three overlapping classes, viz. bicycle, motorcycle and truck, suggested the strong potential about our approach. The evolved CNN model was also tested against real-world traffic video datasets as a case study which resulted into 65% accuracy from a sample of 70 frames from the videos. The use of GE and Bayesian Optimiser also leads to explainability of the proposed approach. The immediate future scope to this approach is to extend the hyperparameters we consider to tune.

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APPENDIX

The datasets used in the experiments and the code for *HyperEstimator* can be found at https://github.com/gauriivaidya/HyperEstimator.