IMPLEMENTATION OF YOU ONLY LOOK ONCE (YOLO) AND SUPPORT VECTOR REGRESSION (SVR) METHODS FOR TRAFFIC DENSITY CALCULATIONS BASED ON AREA OCCUPANCY

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ABSTRACT

This research discusses the implementation of traffic monitoring in calculating the level of traffic density based on the level of service (LOS) value of in homogeneous traffic or heterogeneous traffic. According to previous study, object detection's accuracy is frequently questioned in congested traffic situations. YOLO, on the other hand, can consistently detect objects and is ideally suited for traffic density studies. It is feasible to determine traffic density using a combination of SVR and occupancy area. The total number of training data used by the YOLO method to detect vehicle types was 4665 samples of vehicles consisting of types 1-6. The SVR method uses variables processed using basic freeway segment for training data and occupancy area for test data. The results show that the YOLO method can recognize vehicle types and obtain 75.16% accuracy in daytime traffic conditions. For the estimate of traffic density based on occupancy the YOLO and SVR method is implemented. This is represented with a polynomial kernel with epsilon optimization parameter = 1.0, degree = 1, gamma = 0.0, and coef0 = 2.0 obtaining a MAPE score of 53.59; this value is smaller than the use of a linear kernel getting a MAPE value of 55.5.

Keywords: *Area Occupancy, Traffic Density, YOLO, SVR*

1. INTRODUCTION

Traffic congestion is a situation of stagnation in the vehicle's speed, which is a process of traffic jams. One of the contributing factors is the increase in population which affects the demand for motorized vehicles, according to a survey for the 2014-2018 period showing an increase of 6.49% [1]. As a result, the volume of vehicles passing together exceeds the road capacity [2], [3]. The impact of these problems is low driving speed, time loss, and increased fuel consumption.

Level of Service (LOS) is a quality measure that describes various traffic conditions in vehicle speed, travel time, vehicle freedom in maneuvering, safety, and driving comfort. [4], [5]. The method used to determine road service level is a basic freeway segment with density levels A, B, C, D, E, and F. Density level A represents smooth traffic while level F represents congestion. Measurements on basic freeways analysis use a vehicle adjustment called a passenger car unit (PCU).

Heterogeneous metrics of traffic on the occupancy area have been proposed [6]. Occupancy measurement reflects the different dimensions of the cars on the road and can be applied to heterogeneous situations of road, particularly various situations of road travel.

Large amounts of data have been generated by research on intelligent transportation systems (ITS). Its processing necessitates the use of sophisticated analytical software. The progress of ITS has a positive impact on traffic congestion. Infrastructure for telecommunications, information systems, and road users is linked together [7]. Several advanced

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

traffic management systems (ATMS) strategies have been implemented to solve traffic problems that require dynamic management to provide realtime control [8], [9]. Traffic monitoring systems using video in dynamic scenes are still tricky. Studies conducted in previous research on traffic monitoring include various techniques in detecting, classifying, and counting moving vehicles using sensors or camera. Standard methods of using cameras that are often used include edge detection, blob tracker, a histogram of oriented gradient (HOG), object extraction, and a support vector machine (SVM) for classification. The obstacles faced in identifying objects are when the objects are close or congested, there are shadows, traffic jams, and inappropriate camera angles [10], [11].

Object detection using the YOLO method has been shown to be more effective in experiments, and it can be used for traffic control in fast traffic. Using a camera, the You Only Look Once (YOLO) method of one-shot detection has been effectively applied to counting vehicles and recognizing vehicle kinds in fast traffic [12], [13]. However, it must be improved in order to identify vehicle types, count the number of passing vehicles, and estimate passing vehicle speeds.

Another study refers to using the SVR method to detect occupancy areas in smart buildings [14], by applying several different parameter sets (training data) from the data generated in the EnergyPlus simulation software. SVR helps detect occupancy in smart buildings by setting parameters without the need for high-precision data sets (test data) from EnergyPlus sensors.

The study proposed a new strategy for the density determination based on the calculation of area occupancy using the YOLO and SVR methods. YOLO has been designed for vehicle types detection, vehicle speed estimation, and vehicle time record as it passes. To calculate the estimated traffic density, the SVR approach was developed. The combination of the YOLO and SVR methods for the density calculation should apply to homogenous and heterogeneous characteristics of the traffic.

2. THE PROPOSED METHOD

2.1. System Model

The data processing for traffic density monitoring is divided into three stages: input, process, and output. The input stage is where video files are transformed into frames of images. Performing vehicle detection, developing information on vehicle detection performance, and processing data using basic freeway analysis and occupancy area are all stages of the method. The level of information is the output point, as shown in Figure 1.

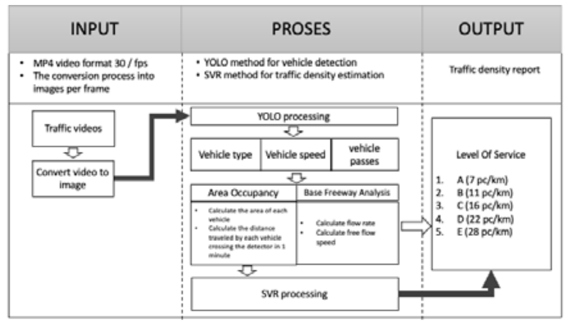

Figure. 1: Model of monitoring traffic density

Each LOS value is a reference to the traffic conditions that occur. Calculation uses a basic freeway segment to determine road service level, as in Table 1.

Table 1: Level of service.

Criteria	LOS				
	A	B	C	D	E
Maximum density (Vehicle / Km)	7	11	16	22	28

2.2. Data Processing

The materials used in this study have been categorized into three categories: reference data, training data, and test data for the YOLO and SVR methods.

2.2.1 Vehicle Dimensions

Table 2 shows basic parameter for determining how many vehicles occupy road space [15].

Table 2: Vehicle Dimensions.

Vehicle Types	**Vehicle information**	**Dimension (m)**	**Vehicle area (m^2)**
1	Sedan, Pick up, bus	4.7 x 1.7	7.99
2	2 (two) axle trucks	5.8 x 2.1	12.41
3	3 (three) axle truck	12 x 2.5	30.00
4	4 (four) axle truck	12.0 x 2.6	31.20
5	5 (five) axle truck	21 x 2.6	54.00
6	Motorcycle	1.75 x 0.7	1.22

2.2.2 Data Annotation

The data used in the YOLO method was collected by direct observation at the one-lane highway location over the course of six hours. The data collection yielded an .mp4 video file format with a 16: 9 aspect ratio (1280 * 720) and a frame rate of 30 frames per second, which is suitable for data annotation. The results are shown in Figure 2.

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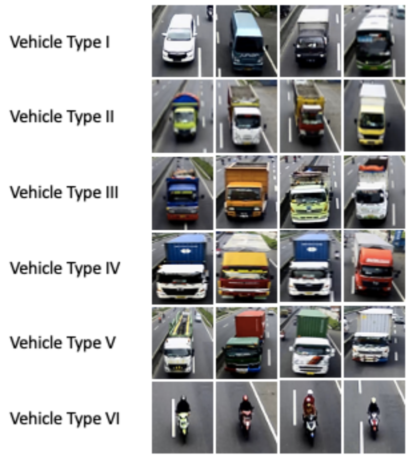

Figure. 2 Type of Vehicle

To obtain different vehicle forms for data annotation purposes, video is converted to images in the form of frames. The method of mapping vehicle data to be recognized by framing objects with coordinate points to be processed in the training process is known as YOLO data annotation. Each vehicle has a different sample picture. Table 3 shows the total number of vehicle images with 20% validation data, which is 4665.

Table 3: YOLO Data Experiment.

Vehicle types	Group	Amount of data
Type I	LV	1804
Type II	LV	731
Type III	HV	159
Type IV	HV	40
Type V	HV	12
Type VI	MC	1919
Total		**4665**

2.2.3 Data Training for Support Vector Regression

As shown in Figure 3, the SVR training data comes from YOLO detection, which breaks down the details into many parameters, including vehicle types, vehicle speed, vehicle dimensions, and travel time.

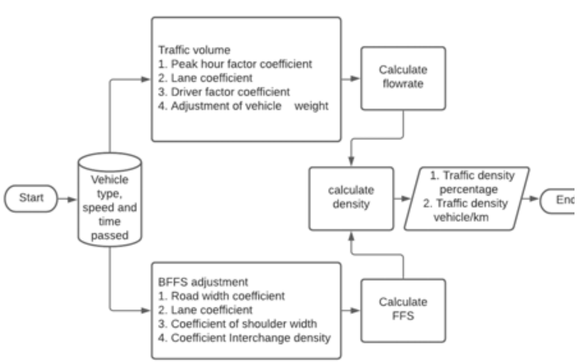

Figure. 3: Data is gathered using the basic freeway segment process

Basic freeway segment measurements are also used as traffic density validation data in addition to being used as training data. Data on the percentage of density and the number of vehicles per km are produced by the simple freeway section. Eq. (1) shows the steps for calculating the peak hour factor (PHF).

$$PHF = \frac{V}{4 * v_{15}} \quad (1)$$

where PHF value is the hourly traffic volume factor, V the average amount of traffic for one hour, v_{15} For 4 x 15 minutes, it has the highest volume. Vehicle Weight adjustment value ae shown in Eq. (2).

$$f_{HV} = \frac{1}{1 + P_T\,(E_T - 1) + P_R(\,E_R - 1)} \quad (2)$$

where f_{HV} represent weight adjustment value E_T and E_R Are passenger cars equivalent to trucks, buses, and recreational vehicles. P_T and P_R are the proportions of trucks, buses, or recreational vehicles in the traffic flow.

A passenger car unit equivalent is calculated according to the Eq. (3).

$$V_p = \frac{V}{PHF * N * f_{HV} * f_p} \quad (3)$$

where, V_p A passenger car unit (PCU) equivalent to traffic flow (pcu/hour/lane), V represents the vehicle's volume, PHF is peak hour factor, N lane number, f_{HV} Adjustment of vehicle weight and, f_p Represents the coefficient influence of the driver's factor.

Calculation of free-flow speed as shown in Eq. (4).

$$FFS = BFFS - F_{LW} - F_{LC} - F_N - F_{ID} \quad (4)$$

where FFS is the free-flow speed, $BFFS$ the essential current speed adjustment value is 110 km / h depending on the type of road, F_{LW} Line width adjustment value, F_{LC} Left shoulder width adjustment value, F_N Value adjustment for the number of lanes and, F_{ID} The value of the spacing between one vehicle and another (interchange density).

Density calculation as shown in Eq. (5).

$$D = \frac{V_p}{S} \quad (5)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

where D represents the density of the vehicle (pc/km/ln), V_p Is flowrate (pc/h/ln), S is the average speed of the vehicle (km / h) [5].

2.2.4 Data Testing with Support Vector Regression

YOLO detection is used to obtain the parameters is to measure traffic density, which include vehicle type, vehicle speed, vehicle dimensions, and time elapsed. Real-time or actual traffic recording data is used. The occupancy area measurement was used to obtain data on the percentage of density and the number of vehicles per km, and the results are shown in Figure 4.

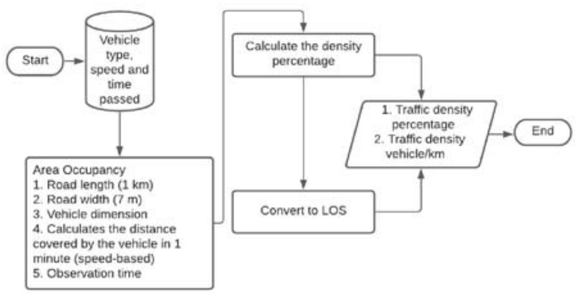

Figure. 4: Data Testing is gathered by the use of area occupancy

In order to calculate density and number of vehicles per km, the occupancy area formulation was used. The estimation measures are as follows Eq. (6).

$$\rho A^{(A)} = \frac{\sum_{i=1}^{N} \frac{L-x_i}{\bar{v}_i} * w_i * l_i}{T*W*L} \qquad (6)$$

$\rho A^{(A)}$ is the occupancy area measured by time and space, L road length, W road width, x_i is the remaining distance traveled by the vehicle while crossing the detector, $\bar{v}_i$ average speed of the vehicle when crossing the detector area (space mean speed). w_i and l_i The length and width of the vehicle and T observation time.

2.2.5 Testing Correlation Variable

Correlation analysis is the basis for decision making that determines whether or not a variable is feasible. The tested variables are used as training data and test data for the SVR process, i.e. the varying number of vehicles which pass the value of the traffic density. Effects of the correlation tests have been processed using the program SPSS by choosing bivariate correlation analysis, Pearson correlation coefficient and significant double-tailed testing. Table 4 shows the findings obtained.

Table 4: Correlation test variable.

		Vehicle Passed	Speed	Density
Vehicle Passed	Pearson Correlation	1	-0.605**	0.981**
	Sig. (2-tailed)		0.003	0.000
	N	22	22	22
Speed	Pearson Correlation	-0.605**	1	-0.543**
	Sig. (2-tailed)	0.003		0.009
	N	22	22	22
Density	Pearson Correlation	0.981**	-0.543**	1
	Sig. (2-tailed)	0.000	0.009	
	N	22	22	22

Correlation testing generated a significance value (sig. 2 tailed) of 0.003 when the relationship between the vehicle traffic variable and the speed variable was measured. The relationship, by comparison, between the variable vehicles passing through the density variable was 0.000. The correlation test value between the three variables is less than 0.005, so the association of the variables can be inferred.

The degree of relationship is measured based on the value of person correlation, namely the cross variable's relationship to the velocity variable of -0.605 and the relationship of the cross variable to the density variable of 0.981. Perfect correlation has a positive direction because it falls within the range of values from 0.81 to 1.0

2.2.6 Grid Search and Cross-Validation for Variable Optimisation

Grid Search and Cross-validation are techniques that can measure the optimal value of hyperparameters. The parameters measured include using the Kernel in the SVR method, including linear and polynomial kernels. The use of the correct parameters will determine the accuracy of traffic density calculations. Testing the optimization of training data parameters consisting of 22 data was tested using the Rapid Miner software. The results are shown in Table 5.

Table 5: Testing hyperparameter.

Kernel	Parameter Name	Parameter Values	MAPE
Linear	Epsilon	1.1475	55.53
	SVM Type	Epsilon SVR	
	degree	91	
Polynomial	Epsilon	1.0	53.59
	SVM Type	Epsilon SVR	
	Degree	1	
	Gamma	0.0	
	Coef0	2.0	

2.2.7 YOLO Training Data

Data training is a data mapping process to help programs identify vehicle types. Data training requires tools with large enough resources. The cloud service application provided by Google, namely Google Colab, can process data training more quickly because it has extensive resources and is accessed for free.

Data training was carried out for 8 hours by performing annotation file training data to produce YOLO prediction .weights files. During the training, various error indicators will be seen. Training should stop when the average loss error value no longer decreases, as shown in Table 6.

Table 6: Testing YOLO data training indicator.

Loop	Average Loss (error)	Rate
2055	0.374933	0.001000

Training data usually reaches 2000-4000 iterations for each object class with an average loss error ratio of 0.05 for small data sheets and 3.0 for large-scale datasheets. The smaller the average loss error, the more precise the detection will be with the ground truth.

2.2.8 YOLO Detection

YOLO uses a single neural network to predict the box and class probability of an image in one- shot detection evaluation. YOLO processes data in image files, divides an input image into an S x S grid, and changes the image size to 448 x 448 pixels.

A single neural network is run simultaneously to obtain various bounding box predictions on the grid cells. Each grid cell consists of 2 (two) bounding box predictions. If an object falls on a grid, the grid cells are responsible for the image's predicted results. Each bounding box produces 5 (five) predictive values: x, y, w, h, and the confidence value. The values (x, y) represent a midpoint on the bounding box in the grid cell. The values (w, h) represent the bounding box's width and height shown in Figure. 5.

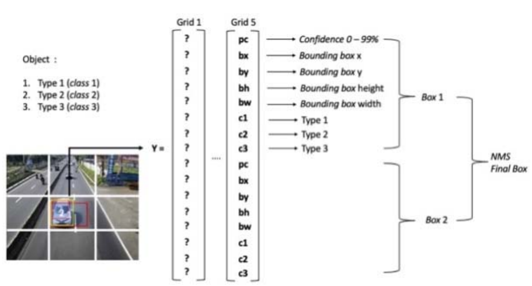

Figure. 5 YOLO Detection System

YOLO has 3 x 3 grid cells. It will produce the equation 3 x 3 x 2 x 8 tensors of the image. YOLO multiplies the class probability (determines the conditional class) and the individual bounding box predictions using Eq. (7).

$$Pr(Class_i|Object) * Pr(Object) * IOU\frac{truth}{pred} = Pr(Class_i) * IOU\frac{truth}{pred} \quad (7)$$

Eq. 7. produces a confidence score in each class precisely so that the predicted bounding box results match the object. Formally YOLO predicts confidence as a prediction of the object according to Eq. (8).

$$Pr(Object) * IOU\frac{truth}{pred} \quad (8)$$

If there is an object, the confidence score will be the same as the intersection over union (IOU). YOLO as seen in Figure 6, predict the bounding box.

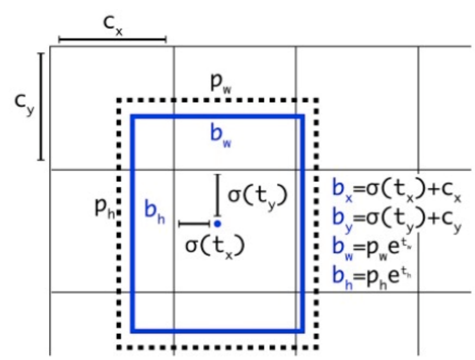

Figure. 6 Predict the Bounding Box with YOLO

YOLO has a prediction framework which is anchor box using cluster measurements. For each bounding box, YOLO Network predicts 4 (four) coordinate points (t_x, t_y, t_w, t_h). If a cell is said to be offset (the bounding box exceeds the cell's boundaries) from the upper left corner of the picture, it is converted by a point (c_x, c_y) and the previous bounding box, which has a height and width, according to Eq. (9).

$$\begin{aligned} b_x &= \sigma(t_x) + c_x \\ b_y &= \sigma(t_y) + c_y \\ b_w &= p_w e^{t_w} \\ b_h &= p_h e^{t_h} \end{aligned} \quad (9)$$

During the training phase, YOLO uses the sum of squared error loss. A ground truth at the predicted coordinates are expressed as $\hat{t}_*$, Then the value is

Journal of Theoretical and Applied Information Technology
15th July 2021. Vol.99. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

equal to the ground truth minus the predicted value. The equation is $(\widehat{t_*} - t_*)$.

2.3. Support Vector Regression

Support vector regression is an algorithm that handles regression problems and can handle overfitting. The aim is to minimize the error value on an estimate-based value. The SVR method for calculating traffic density uses vector input $X = \{(x_1, y_1), \ldots, (x_n, y_n)\} \in X \sqsubseteq \mathbb{R}^d$, A number of moving cars and speeds is vector (x_n, y_n). Density level data shows the scalar output to be $Y = \{(y_{1,} \cdot\cdot, \ldots, y_n)\}$ n denotes the value of training data. The corresponding function is as follows Eq. (10).

$$f(x) = \mathrm{w}^T \varphi(\mathrm{x}) + b \quad (10)$$

The aim of reducing the value of w is to improve the generalization of the function $f(x)$. As a result, the optimization problem solving procedure is as follows Eq. (11).

$$minimize\ \frac{1}{2} \parallel w \parallel^2 \quad (11)$$

With the conditions according to Eq. (12).

$$\begin{aligned} y_i - \mathrm{w}^T \varphi(\mathrm{x}) - b &\leq \varepsilon \\ \mathrm{w}^T \varphi(\mathrm{x}) + b - y_i &\leq \varepsilon \end{aligned} \quad (12)$$

All points are assumed to be within the range $f(X) \pm \varepsilon$ (feasible). Solve the issue of points outside the scope For limited optimisation, variables ξ and ξ^* are needed. The value of C will penalize all points outside the margin as according to Eq. (13).

$$minimize\ \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{\ell} (\xi_i + \xi_i^*)$$
$$depend\ on \begin{cases} y_1 - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (13)$$

The constant value $C > 0$ determines balance achieved between the desired but incompatible features because the flatness at $f(X)$ has a deviation value ε can be tolerated. This is often called the ε-intesitive loss $|\xi|_\varepsilon$.

In the SVR approach, the kernel function is used to solve non-linear problems. Data x (Input Space) is mapped with the Kernel to a larger space. In SVR methods, data is mapped to a higher dimension in order to achieve a better data structure and make classification easier. The efficiency of generalizations will be influenced by the kernel selected.

Linear Kernel as shown in Eq. (14).

$$K(\vec{x}_i, \vec{x}_j) = \vec{x}_i, \vec{x}_j \quad (14)$$

Polynomial Kernel as shown in Eq. (15).

$$K(\vec{x}_i, \vec{x}_j) = (\vec{x}_i, \vec{x}_j + 1)^p \quad (15)$$

2.4. Research Flow

A testing protocol is a set of exercises carried out to address issues seen on the highway. The main goal is to produce the information production, hypothesis development, and testing analysis flow depicted in Figure 7.

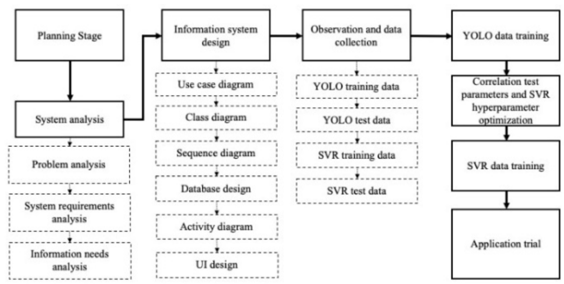

Figure. 7 Research Flow

The testing phase begins with a literature review, and moves on to the system analysis level, the data observation stage, the data gathering stage, and the information system design stage, followed by the assembly of tools for vehicle tracking, data training, traffic data retrieval, estimation, and finally the results are a sequence of processes to accomplish the target.

3. RESULTS AND DISCUSSION

3.1. YOLO Detector Simulation

In this study, YOLO was run with a low-specification computer, and the performance reached 0.41-4 frames per second (FPS), meaning that the detection speed was slower than the actual video speed of 30 FPS as shown Figure 8.

Figure. 8 Results of vehicle detection

YOLO detection's results had a high level of confidence, with an average of 90%. This is very

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

good because every vehicle that is detected is as expected. Vehicle detection testing using the YOLO method, which was carried out for 6 minutes, obtained the results shown in Table 7.

Table 7: YOLO Detection Result.

Vehicle Type	Speed Average (Km/h)	Total		Accuracy (%)
		Actual	YOLO	
1	65	90	102	89
2	43	21	19	90
3	0	4	3	75
4	42	0	0	0
5	0	2	2	100
6	75	136	141	97
			Average	**75,166**

There is a gap between the real number and the YOLO detection results. These factors are shown in Figure. 9.

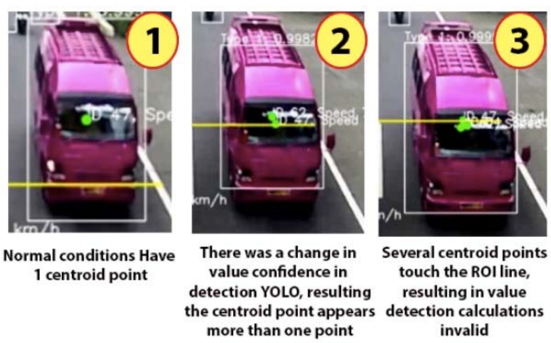

Figure. 9 Results of vehicle detection

The occurrence of a calculation error is caused by a decrease in the confidence value in the YOLO algorithm so that it affects the centroid point tracker, namely the centroid point is not in the bounding box (missing) so that the centroid point does not touch the ROI line or there is more than one point centroid on the bounding box and touches the ROI line.

3.2. Traffic Density Detection

In the SVR procedure, traffic density is calculated by comparing linear and polynomial kernels. The experimental scenario involves matching the reference data (basic freeway segment) to the SVR equation using test data with various kernel configurations. Experiments on traffic density identification were performed out using data collected within 6 hours from 06.00 to 11.00 hours. A margin similar to the reference data indicates the best results. Table 8 displays the traffic density detection equations.

Table 8: Detecting traffic density using a linear and polynomial kernel.

Hour	Basic Freeway Segment Calculations	Kernel Linear		Kernel Polynomial	
	Number of Vehicles / Km	Result	Error	Result	Error
6	10	15,32	0,53	13,9	0,39
7	20	36,3	0,81	30,61	0,53
8	11	17,66	0,60	15,76	0,43
9	11	15,9	0,44	14,36	0,30
10	10	13,89	0,38	12,75	0,27
11	9	11,17	0,24	10,58	0,17
		MAPE	**50,46**		**35,15**

In the SVR procedure, MAPE is used to measure the absolute error percentage. The results show that, with a size of < 50% feasibility, polynomial kernels yield a higher MAPE value than linear kernels.

The MSE (mean square error) calculation can measure the average squared difference between the reference and the test value. The greater the MSE value it's mean farther the actual value is from the test value. Results of calculating MSE linear kernel are shown in Table 9 and Figure 10.

Table 9: Results of calculating MSE linear kernel.

Basic freeway segment	Linear Kernel	Difference	Difference^2
10	15,32	-5,32	28,30
20	36,30	-16,30	265,69
11	17,66	-6,66	44,36
11	15,90	-4,90	24,01
10	13,89	-3,89	15,13
9	11,17	-2,17	4,71
		Total	382,20
		Total/2	**191,10**

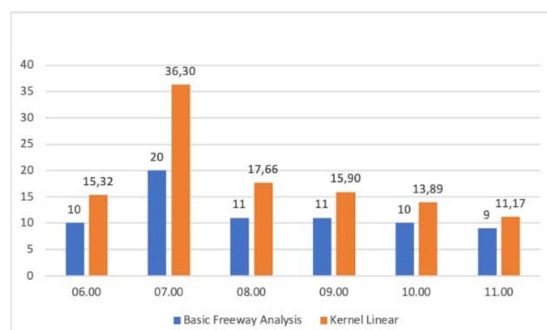

Figure. 10 Graph comparing a basic freeway segment with a linear Kernel

The MSE estimation results for the linear Kernel indicate that the linear Kernel has a cumulative error of 191.10 squared, indicating that the regression model's error rate is reasonably high. Table 10 and Figure 11 show the MSE calculations for the polynomial.

Table 10: Results of calculating MSE polynomial kernel.

Basic freeway segment	Polynomial Kernel	Different	Different ^{2}
10	15,32	-3,90	15,21
20	36,30	-10,61	112,57
11	17,66	-4,76	22,66
11	15,90	-3,36	11,29
10	13,89	-2,75	7,56
9	11,17	-1,58	2,50
		Total	171,79
		Total/2	**85,89**

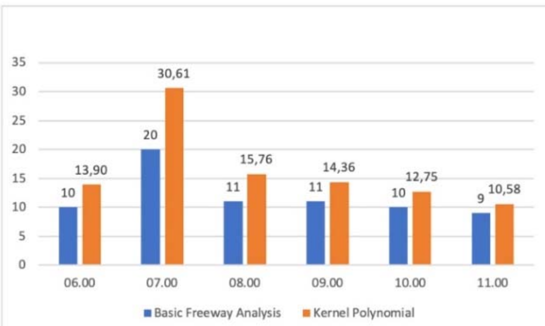

Figure. 11 Graph comparing a basic freeway segment with a polynomial Kernel

A total error of 85,89 is obtained by the MSE value of the polynomial kernel that indicates that the MSE value is low or near zero, which implies that the estimation results are nearer to the actual data.

The difference in the calculation results between the basic freeway segment and the SVR calculation using the linear Kernel and the polynomial Kernel is caused by the difference in the standard value of the parameters used between the number of vehicles passing on the training data (basic freeway segment) using the equivalent of passenger car units. Meanwhile, the number of passing vehicles in the test data using the occupancy area calculation is calculated without converting passenger car units.

The traffic monitoring application combines YOLO and SVR methods, using a computer that has low specifications, based on occupancy area calculation. The results affect the ability of the YOLO method to identify vehicles that move slowly and thus cause stoppages during the detection of vehicles. A computer with high specifications is required for field application in order to perform realtime detection.

Using a polynomial kernel with a value of 53.59, the SVR method's simulation results obtained the lowest MAPE value. Despite the high MAPE value, it can be seen that the graph of the data obtained in the SVR method calculation follows the graph of the reference data. This demonstrates that optimization is needed to equalize the calculation standards so that the training and test data are not too far apart. As a result, the calculated outcomes are very similar to the real results.

4. CONCLUSION

According to the findings, The YOLO approach has a 75.16 % accuracy rate when it comes to detecting vehicle types. When used in bad weather (rainy, cloudy) data annotations of approximately 100 to 200 vehicle data samples are needed for YOLO detecting.

By using a polynomial kernel, the epsilon optimization parameter is set to 1.0, the degree to 1, the gamma to 0.0, and the coef0 to 2.0, yielding a MAPE value of 53.59, which is lower than the 55.5 obtained by using a linear kernel. Compared to the real value (basic freeway segment), the traffic density estimation results obtain an MSE value of 85.89 through a polynomial kernel.

The YOLO traffic density detection simulation is performed on a low-specific computer, 0.51-4 frames per second (FPS) performance detector, meaning that the speed detected is slower than the average standard realtime video detector speed at 30 FPS. so needs computer with propper spesification.

Yolo and SVR combination is helpful not only in the density assessment but also in the traffic effect analysis. Efforts to improve YOLO detection accuracy may be made by expanding the YOLO training data to include all traffic circumstances. In the meantime, selecting SVR technique parameters is extremely crucial to decrease high error value in order to detect the pattern of traffic density, however other more accurate approaches may also be utilized.

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