Exploring diverse prediction models in intelligent traffic control

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ABSTRACT

Traffic congestion is a major challenge that affects excellence of life for numerous people across world. The fast growth in many vehicles contributes to congestion during peak and non-peak hours. The vehicle traffic resulted in many issues like accidents and inefficiency in traffic flow. Many traffic light control systems operate on fixed time intervals leads to inefficiency. The fixed-time signals cause unnecessary delays on roads with minimum number of quantity vehicles. Intelligent transport systems (ITS) introduce new comprehensive framework that combine the advanced technologies to improve the transportation network efficiency and to optimize the traffic management. The high-traffic routes are forced to wait excessively. Machine learning (ML) methods have designed to examine the traffic control. However, the accurate detection and vehicle tracking are essential one for effective ITS. In order to mention these problems, ML and deep learning (DL) methods are introduced to improve prediction performance.

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1. INTRODUCTION

The traffic congestion occurs when road usage increases. Many strategies and techniques based on machine learning (ML) as well as computational intelligence were employed to prevent congestion. Computational intelligence is used for managing traffic and for minimizing the congestion. Computational intelligence is used for handling traffic and for minimizing the congestion. Ant, bee, as well as genetic methods employed for traffic management. With development in computer vision, ML and deep learning (DL) methods are used to identify, recognize, categorize and track the multiple objects in images or videos. With development of technology, various intelligent transport systems (ITS) have increased their desire for automation.

With large development of vehicular communication services, there is elevated stipulate for intelligent transportation scheme to automatically identify the unusual traffic offense and uncontrolled driving on roads. Vehicle localization is an important part for intelligent as well as autonomous schemes like self-driven driving, surveillance and so on. Different vehicle identification techniques are employed widespread with frame differencing, and gaussian mixture model (GMM). Traffic video processing is carried out to follow poignant vehicles as of one frame of image sequence to another frame. With wide-ranging research in automated surveillance systems, high-precision vehicle recognition and tracking is demanding one due to complex road networks and variable illumination conditions. Figure 1 illustrates the advantages of traffic control prediction process. ITS is used to blend network-related data like vehicular cloud computing in a seamless manner for handling the traffic efficiently. The traffic congestion handling solution is categorized as: i) traffic data collection, ii) traffic management, iii) congestion avoidance, and iv) travel time prediction.

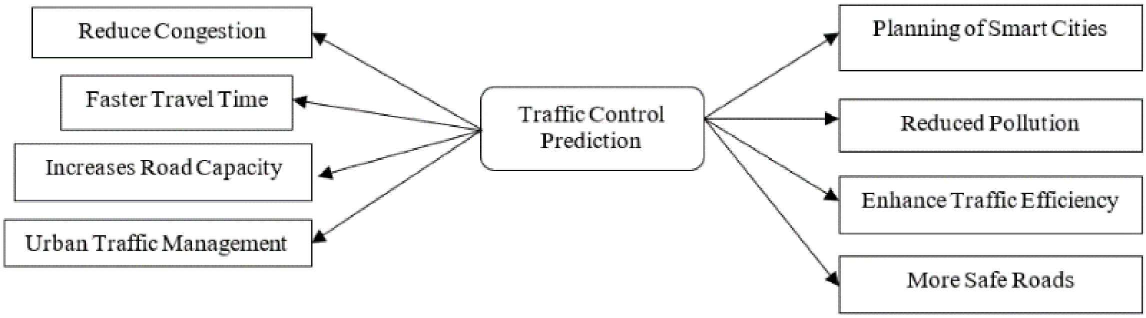

Figure 1. Benefits of traffic control prediction

Figure 2 describes the different processes of intelligent traffic management. The traffic data collection is main and important function in managing traffic management process for accurate traffic prediction. Traffic management system is the process of organizing, arranging, guiding and handling the traffic with moving vehicles and stationary vehicles along with cyclists and pedestrians. Traffic management system guaranteed the safety and effectiveness during movement of people and goods. The designed system increased the environment quality around traffic locations.

Our contribution of the work is given as:

- We predict the intelligent traffic occurrence using different ML and DL methods as well as demonstrate that model carry out enhanced on this database.
- We introduce the intelligent traffic control prediction objectives by six dissimilar ML models and present comparative analysis with conventional models.
- We conduct comparison of results on the intelligent traffic control forecast by dissimilar ML frameworks.

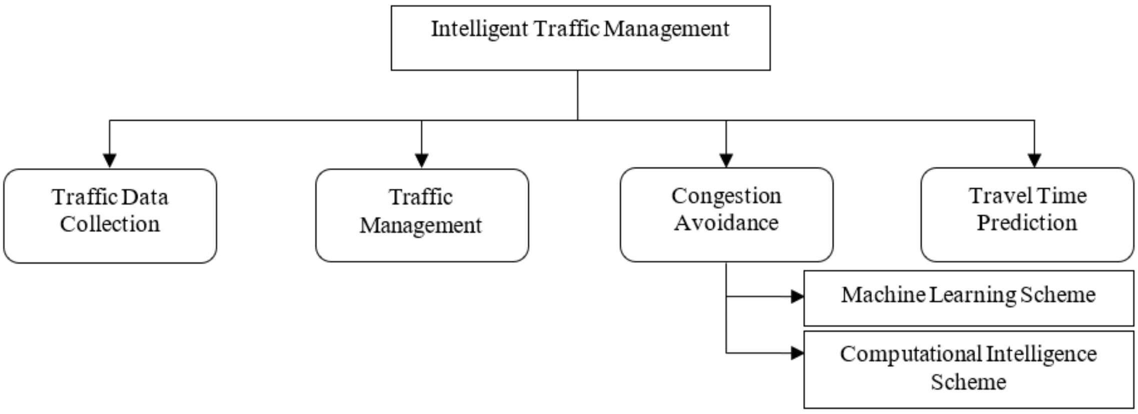

Figure 2. Process of intelligent traffic management

2. LITERATURE SURVEY

A smart traffic control system was developed in [1] which seperate image using extreme gradient boosting (XGBoost) classifier to extort forefront objects from preprocessed image for accurate vehicle detection and tracking. However, it failed to apply DL detectors to increase vehicle detection accuracy. A traffic monitoring and controlling system were developed in [2] to improve accuracy and minimize computation time. However, it faces challenges in traffic monitoring and controlling due to the large availability of images. An automated traffic monitoring system, called TRAMON, was developed in [3] for accurately predicting traffic and tracking vehicle positions. However, the system did not address the issue of time complexity in traffic prediction. A model-based reinforcement learning (RL) method called deep Q network (DQN) was developed in [4] to enhance accuracy of traffic signal control. But the error rate was accurately reduced. End-to-end DL network named PairingNet was developed [5] to improve accuracy of traffic analysis through multiple objects tracking (MOT) and object detection. However, accurate traffic flow prediction remained a challenging issue.

A convolutional neural network (CNN)-based classifier was developed in [6] to improve vehicle traffic flow monitoring through trajectory tracking and object detection. However, it failed to attain highest accuracy in traffic flow estimation. A new ground traffic management approach was introduced in [7] with mobility, flexibility and multiple unmanned aerial vehicles (UAVs). The main aim of designed approach was to enhance the navigation and driving experience through using UAVs that avoid congested routes. CNN-based approach termed LightSpaN was introduced in [8] for vehicle identification with sparse data to attain complex solution. The designed approach minimized waiting time and traveling time with high accuracy. A new framework was introduced in [9] for monitoring highway traffic-stream measures with quality trajectory data. The designed framework comprised the measure that reflects follower driver termed receptiveness angle. A new road traffic noise model (RTNM) was introduced in [10] for dynamically assessing road traffic sound stages as of reliable data. RTNM supported or replaced the noise sensor networks through solving noise pollution concerns. CNN and RL method was designed in [11]. The designed technique reduced the overhead on observed entities with elevated bit rate. The recursive network design was constructed in [12] to monitor traffic flow for anomaly identification. The design increased the cyber-attack detection in SDN. The distributed denial-of-service (DDoS) attack was avoided through eliminating the network forwarding performance degradation. EfficientDet architecture and TensorFlow lite was employed in [13] to employ real-time live video given as of cameras at intersections. The designed architecture carried out instantaneous traffic bulkiness computation through image processing and vehicle detection.

The acoustic noise monitoring system was introduced in [14] for road traffic monitoring with driver safety. The designed system employed vehicle type and weather-related pavement condition depending on audio level measurement. An integrated fog and cloud computing framework was designed in [15] to minimize the latency and network congestion for traffic monitoring. A new bounding box (Bbox)-based vehicle tracking algorithm was designed in [16] with vehicle object patterns collected from highway videos. The ML classifier and CNN classifier were selected real-time highway traffic monitoring system. For smart traffic monitoring and management, the self-powered triboelectric sensor (CN-STS) with electro spun composite nanofibers was introduced in [17]. Transferred charge density was used to address the fast-response and high sensitivity needs for smart traffic management. A low-cost internet of things (IoT) system was designed in [18] for traffic flow monitoring and air quality index (AQI). Traffic flow was performed through video processing in compressed domain. It was determined in real-time over embedded architecture. Air pollution gauge station was computed in [19] to fulfill with values. The contribution was employed to examine the current distribution of air excellence observing stations for road transport. The dynamic updates of traffic noise map was carried out in [20] for noise monitoring with traffic speed data to forecast the noise emission of road network. The traffic speed was employed for affecting traffic noise. The traffic speed was computed to update noise source intensity with real-time noise monitoring data. Supervised learning framework was designed [21] for structural health monitoring (SHM)-sensor-based traffic load estimation. The short recording session was computed from smart camera to label acceleration data with equivalent number of passing vehicles.

Fuzzy incidence graph was constructed in [22] with fuzzy incidence chromatic numbers. Fuzzy incidence coloring monitored the human loss during accidents through adhering to traffic flow laws with minimum traffic flow waiting time. The accident monitoring of chosen area was performed [23] to communicate with the data and showed particular traffic accidents. A single-node traffic measurement scheme termed FlexMon was introduced in [24] to determine fine-grained flows at solitary network node. FlexMon divided the large flows from small ones with flow rules, sketches. ML framework was designed in [25] to find the traffic congestion depending on multiple parameters like delay constraints and speed through GSP vehicle trajectory. A traffic event reporting scheme was designed for efficient event detection and data source reputation mechanisms. Incorporated monitoring platform was introduced. Air quality observing unit combined open-source technology with low-cost and high-resolution sensors. An exponentially-weighted moving average (EWMA) monitoring scheme was introduced in to increase the robustness and minimize the false alarms because of modeling error. IoT based wireless sensor system was designed in with wireless accelerometer for traffic and vehicle classification monitoring. Laboratory tests, field tests and numerical simulation were performed to validate accuracy of monitoring system. An adaptive length (AL) bitmap was introduced in to construct the traffic summary. AL-bitmap created the bitmap with AL for every host. The bitmap length automatically increased with number of hosts.

3. METHOD

Automation as well as intelligent control technologies are manner to revolutionize flow of traffic as well as security in modern transportation schemes that escort to suggested scheme, microcontroller and cameras employed to follow number of vehicles, permitting for time-basis of observing of scheme. Traffic might happen because of weighty traffic jams in intersections. There are diverse traffic administration approaches which intrinsically self-changing to evade congestion.

3.1. A smart traffic control scheme depend on pixel-labeling and SORT tracker

Autonomous vehicle recognition as well as tracking were essential one for intelligent transport management as well as control schemes. Numerous methods were employed to design the smart traffic schemes. The vehicle recognition as well as tracking was carried out through pixel-labeling and real-time tracking. A new smart traffic control system was introduced to partition the image through XGBoos) classifier for extracting the foreground objects. The designed model was partitioned into seven steps. In primary step, every images preprocessed to eliminate the noise. In second step, the pixel-labeling was carried out performed through XGBoost classifier to divide background from foreground. In third step, all pixels classified was extracted and converted into binary image. The blob extraction method was employed to limit every vehicle. In fourth step, intersection over union (IoU) score was computed through detected vehicles with ground truth. In fifth step, all verified vehicles performed visual geometry group (VGG) feature extraction. A unique identifier was allocated to allow multi-object tracking across image frames. In sixth step, the vehicles were counted and classified into stationary as well as moving cars through detecting motion by farneback optical flow algorithm. Simple online and real-time tracker (SORT) was employed for efficient tracking. The designed model increased precision for detection with vision meets drone single object-tracking (VisDrone) dataset.

3.2. Real-time traffic control and monitoring

Congestion has become key problem. An automobile road traffic density is an essential one for enhanced traffic signal control and efficient traffic management. Traffic congestion occurred due to insufficient capability. Capacity limitations as well as demand constraints are connected. Every signal holdup is firm coded as well as traffic independent. An image processing as well as surveillance schemes performed by passenger data, and so on. Moving automobile tracing image provides the quantitative explanation of traffic flow. The real-time live video feeds were used from cameras at intersections to execute instantaneous traffic bulkiness computations through image processing and vehicle detection with help of EfficientDet architecture and TensorFlow lite. The main objective of the architecture was to minimize the traffic jams and accidents that switch signal lights based on vehicle density on road and priority set for particular emergency vehicles. The designed architecture presented the people with safe transportation, reduced fuel consumption and waiting time. Vehicle recognition was performed during system from images. The recognition was not performed during electronic sensors mounted on roadway. The camera installation was performed next to traffic light that gathered the video feed sent to Raspberry Pi. The designed architecture handled the traffic light timing to perform automatic control of traffic situations.

3.3. TRAMON: an automated traffic monitoring system for high density, mixed and lane-free traffic

Traffic congestion is considered as the key problem in cities. Traffic data like traffic mean speed, flow, density and travel time identifies the traffic congestion hotspots and attains the potential solutions. Traffic data are gathered through human surveyors, road tubes, induction loop and piezoelectric sensors. The designed method collected the data with minimal maintenance costs. With development in traffic data collection, the computer vision originated with availability of DL. Video and image processing using DL extracted macroscopic data and microscopic data. Novel visual database approach was introduced for assisting TRAMON in enhanced density, assorted as well as lane-free traffic. An advanced DL algorithm was introduced to identify and track the vehicles from traffic videos. The designed monitoring methods presented accurate traffic monitoring in mixed traffic. The mixed traffic flows in developing countries comprised vehicles types. The computer vision algorithms experienced difficulties in identifying and tracking the high density of vehicles. A comprehensive framework was employed to train deep-learning-based computer vision algorithms detecting the vehicles in high density, heterogeneous and lane-free traffic.

3.4. Image-based traffic signal control via world model

With growth of intelligence technologies, traffic signal control performed renovation as of the predetermined-time control to proactive control. A fixed-time controller phase sequence and duration were pre-determined through professional engineers through experience or rules. Traffic signal control was shifted as of passive to proactive controls for allowing controller to straight present traffic flow to attain destination.

An effective prediction model was required for performing signal controllers. An image was employed with vehicle positions to explain the intersection traffic states. A model-based RL method termed DreamerV2 was introduced foe learning-based traffic world analysis. The traffic world model explained the traffic dynamics in image form. The designed model was employed as abstract alternative to create multi-step planning information. World method was employed to forecast the impact of diverse control behaviors on future traffic conditions.

3.5. PairingNet: a multi-frame based vehicle trajectory prediction deep learning network

Traffic data collection as well as investigation are considered as essential elements for real-time administration of transportation networks. ITS was employed to perform accurate and cost-effective techniques for traffic data collection. UAV with video streaming capability covered wide area, minimized installation cost as well as errors. UAV supported by image processing gathered microscopic traffic information like vehicle type, direction, trajectory, speed, and driving behavior. An intelligent image processing techniques were necessary for recognizing and tracking the objects gathered in the UAV videos. City traffic infrastructure required evaluation and enhancement through large quantity of data analysis. The construction and laborious work performed vision enhancement in traffic analysis. Among diverse intelligent transportation system, MOT was carried out. MOT was employed in traffic analysis with vehicle speed, movement direction as well as consideration of single factor in trajectory tracking. An end-to-end DL network termed PairingNet was introduced. PairingNet combined the vehicle trajectory to network during feature synthesis of successive images. PairingNet was designed to forecast progress direction as well as vehicle speed through retaining function and accuracy. In designed network, additional features were used to track the vehicle trajectory. A pipeline was used to minimize the loading latency acquired through consecutive frames for PairingNet. PairingNet increased the accuracy rate during vehicle trajectory planning.

3.6. A real-time vehicle recognition and new vehicle tracking schemes for determining and monitoring traffic on highways

Real-time highway traffic monitoring systems was an essential problem in road traffic administration and so on. The traffic monitoring system depends on online traffic flow from time-dependent vehicle trajectories. Vehicle routes were extorted as of vehicle recognition and data tracking attained through road-side camera image processing. You only look once (YOLO) was favored as it present elevated frames per second (FPS) concert as well as object localization functionality. The designed system increased the vehicle classification accuracy for traffic flow monitoring. The Bbox-based vehicle tracking algorithm increased the vehicle classification accuracy of YOLO. A new vehicle dataset was gathered with the object patterns gathered from highway videos.

3.7. Dataset used

For conducting the experiment analysis, traffic image dataset is used. The name of the dataset is traffic images of vehicles. The URL of the dataset is https://www.kaggle.com/datasets/therealshihab/traffic-detection-for-yolov5. Traffic images of vehicles dataset comprises the set of train and validation images with labels of traffic condition in Dhaka city for traffic image detection. The capital city of Dhaka has only 7% traffic roads in existence of around 8 million computers day. Situation of Dhaka traffic is distinctive with insurmountable challenge for traffic management systems to control and maintain the smooth flow for many vehicles. An automation of traffic process is most optimal route to avoid the issue using advances in artificial intelligence (AI)-based technology. A self adaptive city traffic control system is carried out based on object detection and DL.

3.8. Evaluation metrics

It is important to compute the traffic control prediction performance for identifying how accurately the predicted results match the actual ones. Evaluation metrics are used to compute the traffic control prediction model. The metrics choice depends on model type. Prediction accuracy, prediction time and false positive rate (FPR) used to calculate traffic control prediction. Traffic control prediction accuracy (TCPA) is described as ratio of number of traffic images that are accurately predicted to total traffic images. It is computed in percentage (%). When prediction accuracy is higher, the method is more efficient. FPR is described as the ratio of the number of traffic images that are incorrectly predicted. It is computed in percentage (%). When the error rate is lesser, the method is more efficient. The traffic control prediction time (TCPT) is described as product of number of traffic images and amount of time consumed to predict one traffic image. It is measured in milliseconds (ms). When the TCPT is lesser, the method is more efficient.

$$\mathrm{TCPA} = \frac{\text{number of traffic images that are accurately predicted}}{\text{number of traffic imges}} * 100 \tag{1}$$

$$\text{FPR} = \frac{\text{number of traffic images that are incorrectely predicted}}{\text{number of traffic imges}} * 100 \quad (2)$$

$$\text{TCPT} = \text{number of traffic imges} * \text{Time(predicting one image)} \quad (3)$$

4. RESULTS AND DISCUSSION

The result is calculated in TCPA, TCPT, and FPR by using different classification methods. The result depends on how accurate proposed model gets trained. The overall performance results measures are shown in table and graphs.

In Table 1, evaluation of different traffic control prediction techniques is carried on traffic image dataset. The table attained the accuracy values of 86.25% to 96.86% on original dataset. New smart traffic control system has attained least accuracy of 86.25%. Traffic monitoring system has produced highest TCPA 96.86% on traffic image dataset. The TCPT values ranges from 29 ms to 55 ms. Traffic monitoring system consumed lesser TCPT than conventional methods. The learning curves of all existing methods with traffic image dataset describe the traffic control prediction results.

Table 1. Overall results for traffic contro prediction method

Existing techniques	TCPA (%)	TCPT (ms)	FPR (%)
New smart traffic control system	86.25	55	13.75
EfficientDet architecture	88.92	51	11.08
Visual dataset framework	91.56	45	8.44
DreamerV2	92.78	40	7.22
PairingNet	95.21	36	4.79
Traffic monitoring system	96.89	29	3.11

Figure 3 illustrates the learning curve of new smart traffic control scheme with traffic images of vehicles. The graph shows the training score and validation score for diverse number of training examples. When the training examples are lesser, the cross-validation score is ‘0.75’ and training score is ‘0.99’. When the training examples get increased, the cross-validation score gets slowly increased and reaches the value ‘0.84’. The training score gets slowly reduced and reaches the value ‘0.86’.

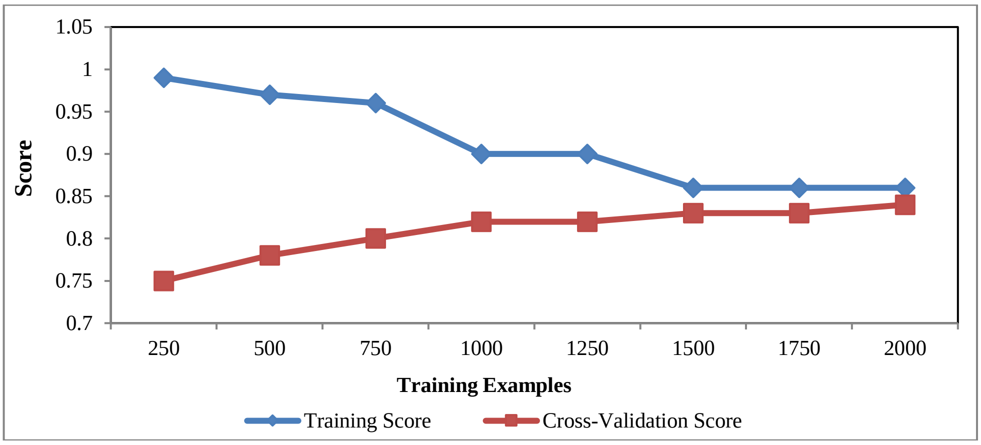

Figure 3. Learning curve of new smart traffic control scheme with traffic images of vehicles

Figure 4 illustrates the learning curve of EfficientDet architecture with traffic images of vehicles. The graph shows the training score and validation score for diverse number of training examples ranging from 200 to 2,000. When the training example is 200, the cross-validation score is ‘0.8’ and training score is ‘0.95’. When the training examples get increased to 2,000, the cross-validation score gets slowly increased to the value ‘0.86’. The training score gets slowly reduced and reaches the value ‘0.88’.

Figure 5 illustrates the learning curve of visual dataset framework with traffic images of vehicles. The graph shows the training score and cross validation score for diverse number of training examples ranging from 200 to 2,000. When the training example is 200, the cross-validation score is '0.82' and training score is '0.99'. When the training examples get increased to 2,000, the cross-validation score gets slowly increased to '0.90' and the training score gets slowly reduced and reaches the value '0.91'.

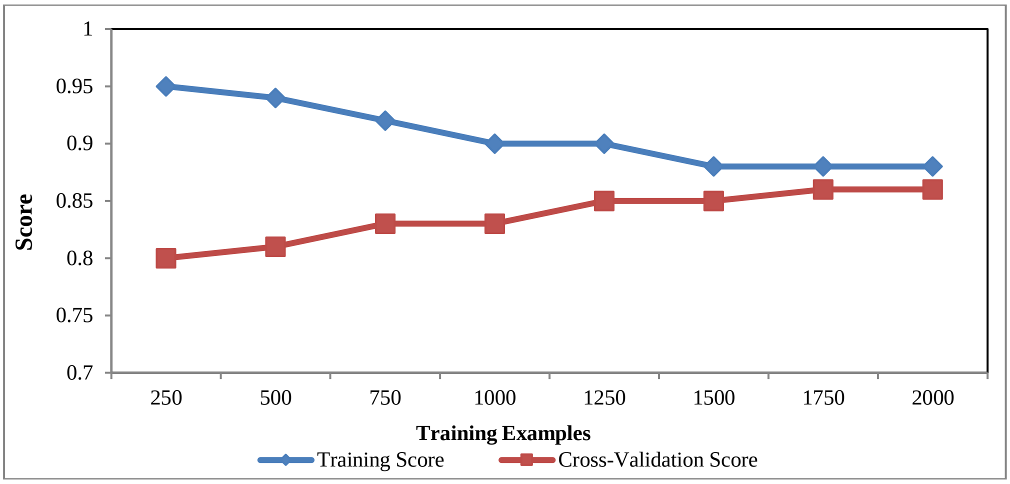

Figure 4. Learning curve of EfficientDet architecture with traffic images of vehicles

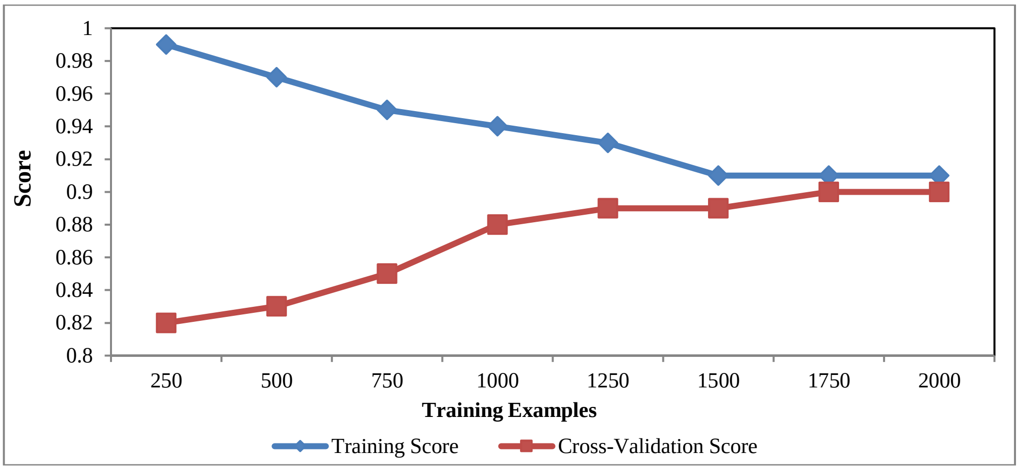

Figure 5. Learning curve of visual dataset framework with traffic images of vehicles

Figure 6 illustrates the learning curve of DreamerV2 with traffic images of vehicles. The graph shows the training score and cross validation score for diverse number of training examples ranging from 200 to 2,000. When the training example is 200, the cross-validation score is '0.85' and training score is '1'. When the training examples get increased to 2,000, the cross-validation score gets slowly increased to '0.90' and the training score gets slowly reduced and reaches the value '0.92'.

Figure 7 illustrates the learning curve of PairingNet with traffic images of vehicles. The graph shows the training score and cross validation score for diverse number of training examples ranging from 200 to 2,000. When the training example is 200, the cross-validation score is '0.88' and training score is '0.99'. When the training examples get increased to 2,000, the cross-validation score gets slowly increased to '0.94' and the training score gets slowly reduced and reaches the value '0.96'.

Figure 8 symbolizes the learning cures of traffic monitoring system with traffic images of vehicles. The graph shows the training score and cross validation score for diverse number of training examples ranging from 200 to 2,000. When the training example is 200, the cross-validation score is '0.89' and training score is '0.99'. When the training examples get increased to 2,000, the cross-validation score gets slowly increased to '0.94' and the training score gets slowly reduced and reaches the value '0.95'. From the learning curve, the traffic control prediction accuracy values are obtained.

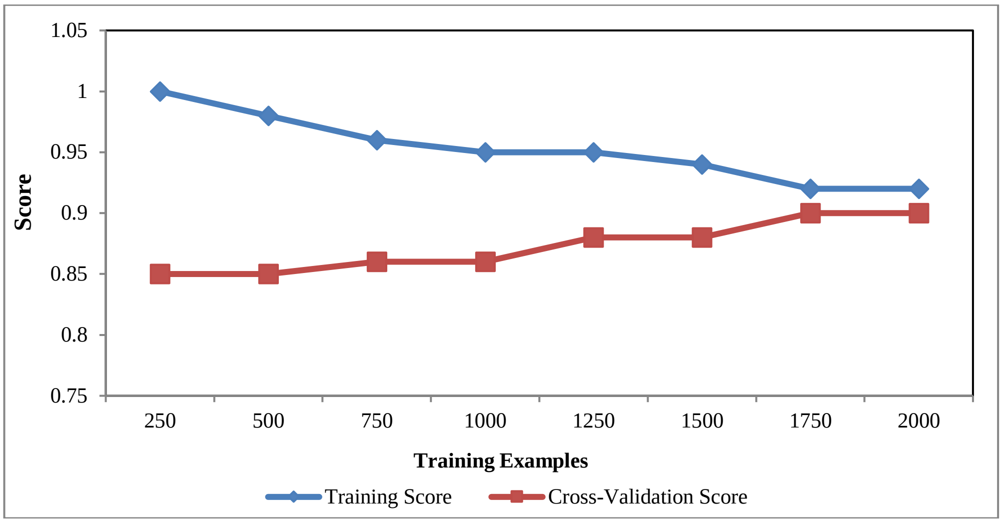

Figure 6. Learning curve of DreamerV2 with traffic images of vehicles

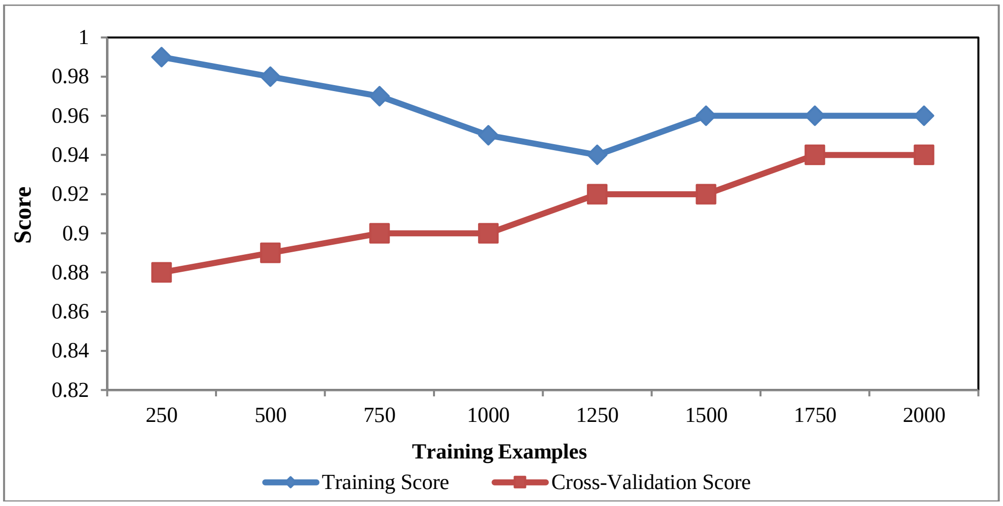

Figure 7. Learning curve of PairingNet with traffic images of vehicles

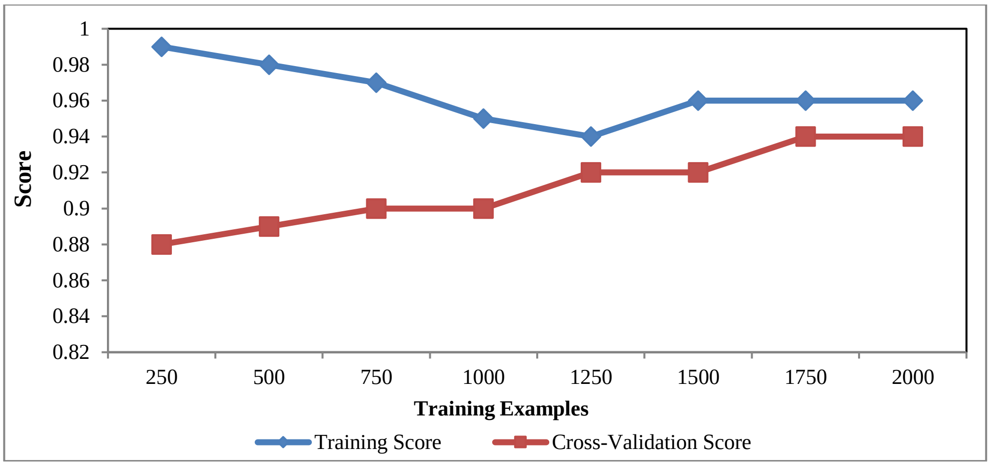

Figure 8. Learning curve of traffic monitoring systems with traffic images of vehicles

5. CONCLUSION

Several research was performed on traffic management system. Intelligent traffic monitoring is an active research topic because of emerging technologies like IoT as well as AI. The integration of technologies was employed for decision making and attained urban growth. In this work, traffic control prediction was attempted using diverse ML techniques. Three performance parameters were used to analyze results of designed models implemented for traffic control prediction with traffic image datasets. When comparing the result with another recent study, traffic monitoring system has produced highest traffic control prediction accuracy of 96.89% than other five existing methods. These outcomes powerfully propose which gradient transfer learning model can be implemented for traffic control prediction instead of the other existing ML classifiers.

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