Smart Fleet Management System Using IoT, Computer Vision, Cloud Computing and Machine Learning Technologies

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Abstract—**The objective of this paper was to present the effective use of niche technologies in solving most critical problems of Fleet Industry. The proposed fleet management system described in the paper used a rich set of technologies like Internet of Things(IoT), Cloud Computing, Computer Vision, Machine Learning, Deep Learning and Embedded. IBM Watson IoT and Heroku platforms hosted the application to receive data from vehicle dashboard device. Driver's face authentication and driving pattern monitoring, Fuel Consumption prediction modules used OpenCV (Computer Vision), SVN (Machine Learning) and CNN (Deep Learning) techniques. Vehicle's Telematics, deviation from route, unauthorized entry in the container, continuous monitoring of trucks internal environment was handled by a high end embedded device with a set of sensor box, cameras, OBD-II device and a gateway. Real data was collected to train and test the face detection and authentication models used in the system. Simulation results demonstrated that the proposed approach can achieve realistic demand of handing and manipulating humongous data coming every few seconds from several vehicles through IoT, NoSQL CloudantDB database and Cloud Computing. The paper also presented the architecture of the system and experimentation results done for various modules of the system.**

Keywords—Fleet, Open Face framework, linear SVM classifier, OpenCV, eye-blinks detection, eye aspect ratio, EAR, Neural Networks, CNN, traffic signal identification, traffic sign identification, ORB-II, Raspberry Pi, Gateway, IoT, Computer Vision, IBM Watson, Bluemix

I. Introduction

Fleet managers face several difficult challenges every day[1][2].

Technology has now advanced to the point where many of

challenges can be solved. This paper describes a latest features and

technology rich Fleet Management Solution built at Persistent Systems

Limited. Below are the key business requirements of

Fig. 1. Crucial Fleet Management Features

The four Main Challenges Faced by Fleet Industry is –

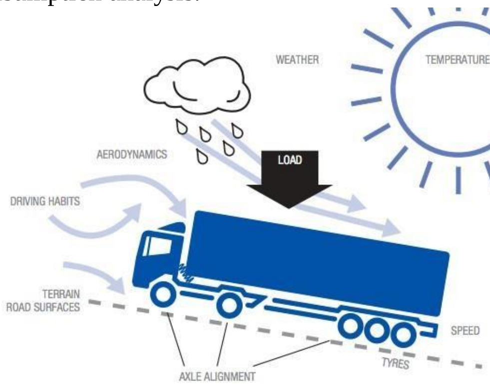
A. *Driver safety/behavior*

In the Fleet Accident Management Survey conducted by CEI in 2016, it was found the that most common kind of accident that fleet drivers face is being rearended. That's not surprising; there is an increase in the number of rear-end accidents among all drivers. Common causes of the Accidents are Over Speeding, violating traffic rules (jumping signals, not following traffic signs), violating lane discipline, driving in influence, not taking breaks, eating or using mobile phones. There are huge expenses associated with fleet accidents, including property damage, insurance increases, worker's compensation claims, reduction in productivity, and potentially even third-party lawsuits. Making sure that only the authorized driver is operating the vehicle is also a vital problem to solve.

B. *Fuel costs and efficiency*

[3] Ability to model and predict the fuel consumption is vital in enhancing fuel economy of vehicles and preventing fraudulent activities in fleet management. Fuel consumption of a

vehicle depends on several internal factors such as distance, load, vehicle characteristics, and driver behavior, as well as external factors such as road conditions, traffic, and weather. However, not all these factors may be measured or available for the fuel consumption analysis.



Fuel environment affecting parameter

C. *Fleet Tracking and Theft*

!.

There is the reality (or the risk) of vehicle theft.

Ultimately, tracking systems allow you to a simple question – “where my vehicles are?” Check on the vehicles in the event of a crisis ranging from a major accident on a main road to an unexpected extreme weather event, a crisis can put both drivers and vehicles in danger. Fleet tracking helps to quickly know if there are any assets in an effected area, providing the ability to take actions if necessary. Immediate alerts are necessary in case of Vehicle deviating from specified route or halts for a longer duration at some location.

Perishables (such as pharmaceuticals, food, and plants). It's a word that can make any shipping manager or logistics provider cringe. The loss of perishable goods in transit means lost revenue. Truck containers need to maintain a constrained environment like temperature, humidity, light intensity etc. to keep the material fresh for a longer duration. Less damage of your perishable goods, resulting in fewer customer complaints and lower costs due to a reduction in replacing broken items. It is difficult to identify who and when enters the vehicle and send immediate alters in case of vehicle door opening and unauthorized location.

D. Material Damage and Identifying Fake vs Genuine Customer Insurance Claims

Delays, material damage and thefts lead to customer insurance claims and can incur huge loss to the business. As there is lack of data of fleet on the go, identifying fake vs genuine customer claims are tough.

The paper provides in depth explanations of the technologies used by the Fleet solution to solve above mentioned problems in the upcoming sections of the paper.

II. METHODOLOGY

The major features of the fleet management system are –

Screens below show the Glimpse of the system:

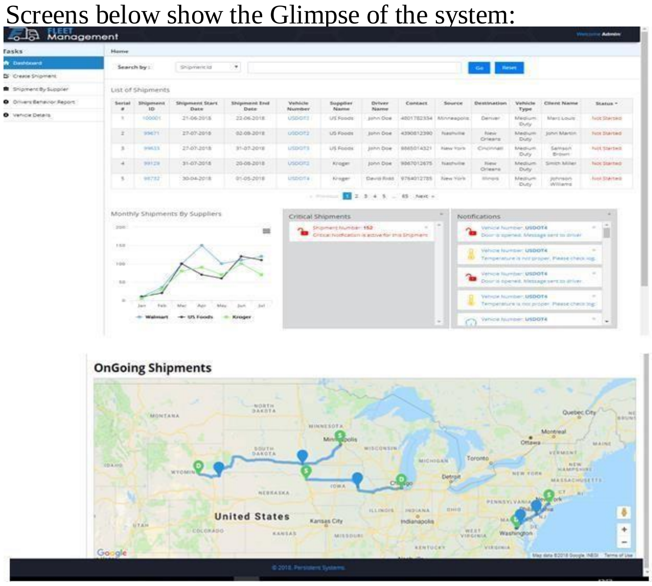
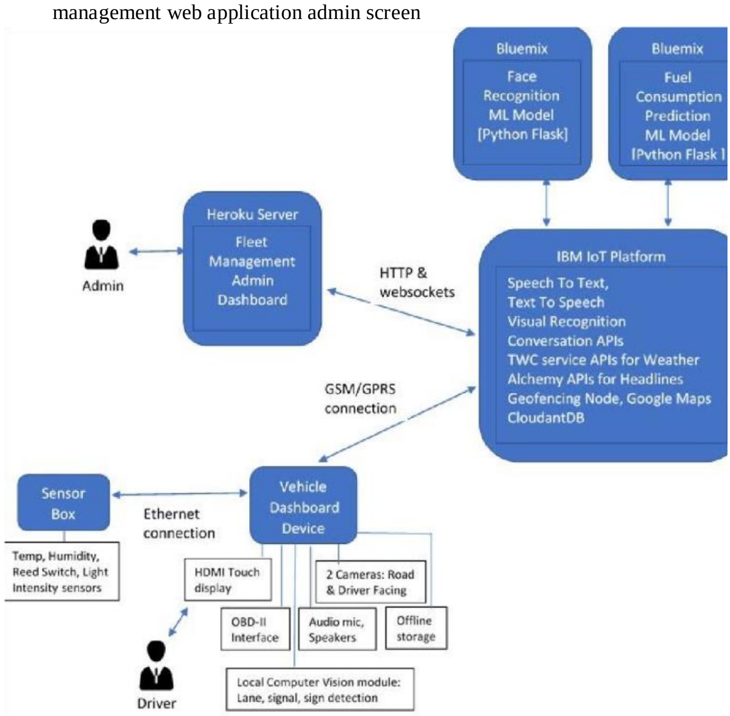


Fig. 3. Fleet management web application admin screen



III. SOLUTION ARCHTECTURE

Fig. 4. Fleet management system architecture

Architecture diagram shows how various components of the solutions are hosted on different servers like Heruko, Bluemix and local gateway on vehicle device. All components and modules will be explained in the upcoming sections.

IV. CHALLENGES AND SOLUTION

Below section provides in depth information on how the each of the five challenges mentioned in the introduction section is solved using various technologies.

A. Challenge A: Driver safety/behavior (IoT, Machine Leering, Computer Vision, ChatBot & Cloud)

Solution:

Technologies IoT, Machine Learning, Computer Vision, chatbot and cloud helped to make advancement in system to provide better vigilance to operator. Following are the technology usage in the system to solve the problem.

a. *Driver Face Authentication*

Driver Identification has always been problematic. Driver assignment is normally done by assigning: keys, RFID badges, cards, or codes entered by each driver. Besides the fact that these are often lost or stolen, it does not fix the problem of who is really operating the vehicle as they can be passed between drivers.

Face authentication module comprised of finding live face detection through eye blinks to avoid a situation of driver using someone else's photograph for authentication. And then recognizing the captured image of the live face of the driver. Driver can start the vehicle only after successful authentication. Driver will receive key in the form of SMS to start the shipment after successful face recognition.

[4] An extensive comparative study of various facial detection and recognition techniques was performed. A two-phase process for facial recognition was chosen:

1) *First phase is the detection phase:* which comprises the following two steps: Step one Face detection in a webcam input and capture frames using OpenCV step two Detect eye-blinks using eye aspect ratio method on captured frames to identify if it is a live person's face or no.

Results showed that the eye blinks are consistently well captured in high-resolution closeup image using EAR (Eye Aspect Ratio) than OpenCV Haar-cascade method.

2) *The second phase, Face recognition:* for recognizing the face captured from phase one, comprises of the below steps:

Step one: Finding face in the frame captured by the camera using dlib's frontal face detection using HOG face pattern.

Step two: Handling faces looking in different directions using by dlib's 68_face_landmarks

Step three: Generating 128-embeddings for faces by extraction of few basic measurements for each face such as size of each ear, the spacing between the eyes, the length of the nose, etc. After extracting these basic measurements for each face, CNN (Convolutional Neural Network) was used to find the facial features best suited for recognizing the face. CNN, when trained, generated close to 128 measurements for different images of a single person.

Step four: Recognition of the person: For this step, a comparison of 5 common classifiers was performed with the available dataset of captured images. Linear SVM classifier was proposed citing better prediction accuracy among all classifiers:

TABLE I. COMPARISON RESULT OF COMMON CLASSIFIER

Classifier	**Training Data ***	**Test Data ***	**Correct prediction**	**Incorrect prediction**
LSVM	3240	1400	35	0
DBN	3240	1400	0	35
Decision Tree	3240	1400	7	28
Gaussian	3240	1400	12	26
RSVM	3240	1400	33	2

*Training Data ❼(81x40 = 3240) 81 employees with 40 images each, Test Data ❼(35x40=1400) 35 employees with 40 images each

Experiments to find the most accurate face recognition model for the given use case was conducted at Persistent Systems Pune and Nagpur weeks over 8 weeks. OpenFace algorithm with dlib in contrast to earlier approaches of using TensorFlow Inceptionv3 model and IBM-VR. Experiments were done with the help of 14 employees with 150 images each, covering 24 different variations such as straight face, tilted face, varied facial expressions, holding phone, with headsets, different hair styles, etc. in the data set. OpenFace with dlib gave the most accurate results with good confidence distribution scores for top 5 predictions. Experiments were also performed to find the accuracy of the selected (OpenFace with dlib) model. Accuracy of the face recognition model proposed

was computed by live face recognition activity, CT1 conducted with – 223 employees, 40 images each & CT2 – 81 employees, 80 images each; of Persistent Systems Ltd. at Pune and Nagpur locations respectively.
This activity was conducted in following phases:
1. Data collection and training of the model 2. Testing the trained model with the images captured.

Data collection was conducted over a period of two weeks at both the locations. For everyone, 40 images for CT1 and 80 images for CT2, were captured and fed to the model for training. For individuals with & without spectacles were captured. All the images for an individual were frontal or straight face and slightly tilted images. Total number of images used to train models for CT1 - 8920 and CT2 - 6480.

Fig. 5. Application screen with 2 faces, 1st in and 2nd out of boundry

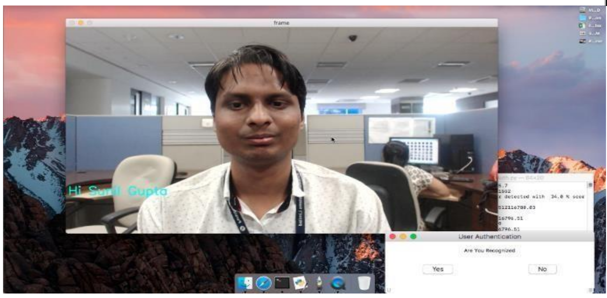


Fig. 6. An individual with correct prediction pop-up dialog requesting user input for crowd testing

TABLE II. ACCURACY AND THRESHOLD COMBINATION REPORT

Location	Accuracy of the model	Threshold
Pune	93.32% *	None
Nagpur	92.47% *	None
Pune	78.79% **	15.19%
Pune	78.415% **	10%

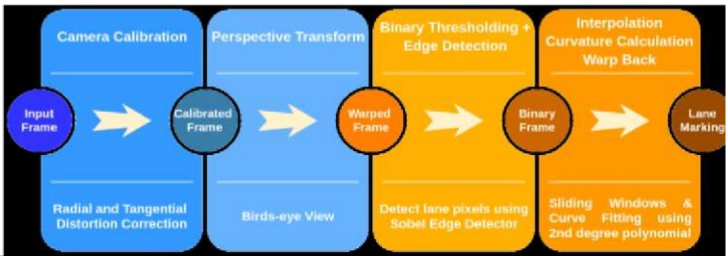
* (total positive cases *100)/total tested cases)
** (for total positive and negative cases)

Detailed experimentation results can be found in the paper[4].

b. Identification of driver's driving patterns & traffic rule violations through vision techniques & OBD Telemetics: (Opencv-Sobel Edge Detector, HOG, SVM, SSD MobileNet CNN)

OBD-II provides useful data for On Board Diagnostics about driver's driving patterns and engine usage and health. Most Fleet Management solutions gather data from OBD device and process it to get meaningful insights about drivers and vehicles on the road. The mentioned Fleet management system also does same. It has a configurable rule engine which decides driver rating based on OBD parameters.

However, OBD data does not cover driver's traffic violation based on traffic signs [7] and signals. The Salient feature of the solution covered in the paper is the collaboration of OBD data with Computer Vision techniques [9] to detect highway lanes, traffic signals and signs. It also detection other vehicles in front using front view camera of the vehicle dashboard device. [5][6]



I. Lane Departure Detection: For the detection of lane, marking lines and calculation of curvature of the lane, distance from the centre of the lane following approach is used

i) Compute the camera calibration matrix and distortion coefficients given a set of camera images.

ii) Apply the distortion correction to the raw image. iii) Use colour transforms, gradients, etc., to create a threshold binary image. iv) Apply a perspective transform to rectify binary image (" birds-eye view").

v) Detect lane pixels and fit to find lane boundary.
vi) Determine curvature of the lane and vehicle position with respect to centre.
vii) Warp the detected lane boundaries back onto the original image.
viii) Output visual display of the lane boundaries and numerical estimation of lane curvature and vehicle position.

Fig. 7. Lane Departure Detection Algorithm

II. Vehicle Detection:

recurring detections frame by frame to reject the outliers and follow detected vehicles.

v) Estimate and draw bounding box for vehicles detected.

Dataset used to train the model & Image specifications: KITTI Vision Benchmark suite, Training samples-4000, Testing samples -3425, Size of each image-64 X 64 .jpeg (Joint Photographic Experts Group)

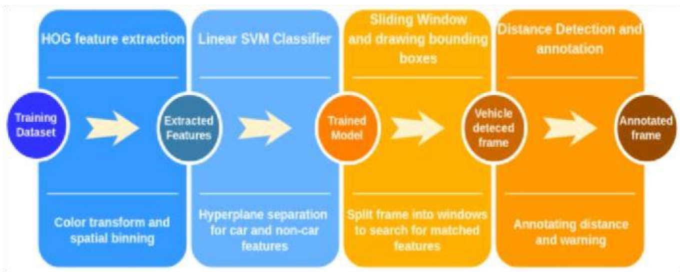


Fig. 8. Vehicle Detection Algorithm

III. Traffic Signal and Sign Detection

Two models were tried for this module. First Module: Traffic Sign Detection and Classification: For detecting traffic signs and classification following approach is used[6]

i) Load the data set.
ii) Explore, summarize and visualize the data set. iii) Design, train and test a model architecture. iv) Use the model to make predictions on new images.
v) Analyse the softmax probabilities of the new images.
vi) Dataset used to train the model: GSTRB, Training samples- 39209, Testing samples- 12360, Size of each image- 32 X 32 ppm (Portable pixmaps)

Second Module: Traffic Signal Detection using Template Matching. (using Python OpenCV)[7][8]

i) Load an input image and its image patch (template) ii) Perform a template matching procedure by using the OpenCV function match Template. iii) Normalize the output of the matching procedure
iv) Localize the location with higher matching

For detecting passer-by vehicles following approach is used

i) Perform a Histogram of Oriented Gradients (HOG) feature extraction on a labelled training set of images and train a Linear SVM classifier.
ii) Apply a colour transform and append binned colour features, as well as histograms of colour, to your HOG feature vector. iii) Implement a sliding-window technique and use trained classifier to search vehicles in images. iv) Run pipeline on a video or live camera stream and create a heat map of

The module was thoroughly tested with sample road and highways videos. Live camera feed of the road . And with a model road set up having lanes, traffic signals, signs & a camera mounted on a vehicle chassis. Following are some results _

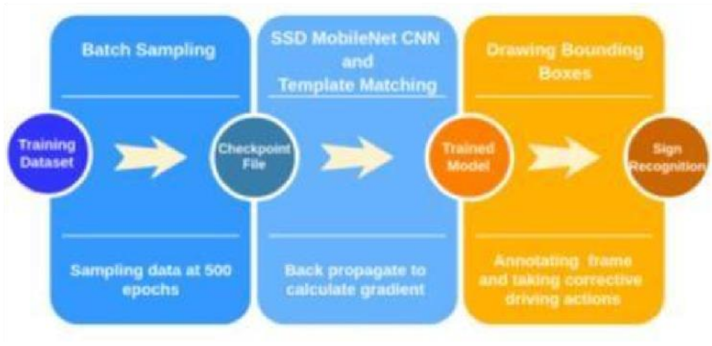


Fig. 9. Traffic Signal and Sign Detection Algorithm

probability

v) Draw a rectangle around the area corresponding to the highest match

Fig. 10. Lane Departure Algorithm results with curvature and center offset

Fig. 11. Vehicle Detection Results

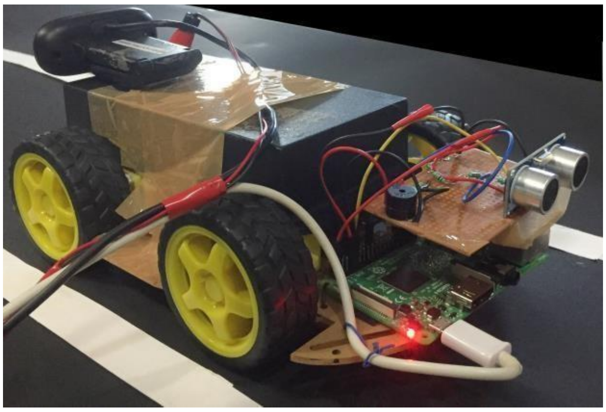


Fig. 12. Autonomous Vehicle used for experimentation

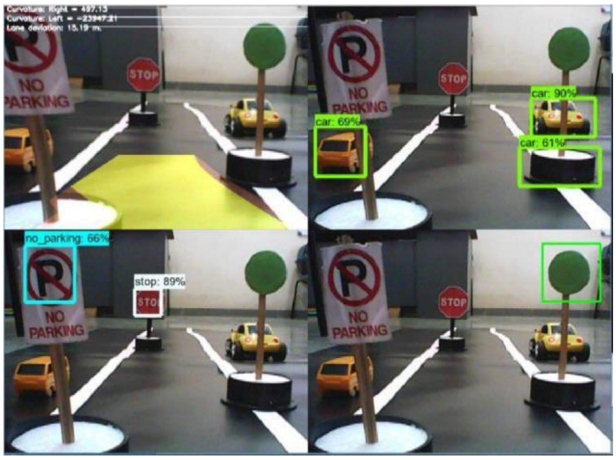


Fig. 13. Traffic Signal, Sign, Lane and Vehicle detection modules experimented on a dummy road setup

c. *Driver Safety & Assistance dashboard*
Provides a chatbot and displays front camera view with Lanes marking, signal, signs, vehicle detection and Lane departure warnings. It also suggests nearby fuel stations in map view, prompt for driver for breaks, provides immediate feedback on rule violation and display his driving score.

Fig. 14. Driver dashboard screen

B. Challenge B: Fuel Cost and Efficienecy (Machine Learning & Cloud)

Solution:

The Fleet Management solution also has a machine learning Fuel consumption prediction module. There are broadly three categories which affect the fuel consumption. Driver, Truck and weather conditions. There was a lack of real data, hence the data is simulated for this module. The experimentation showed the important factors influencing fuel consumption and correlation between various factors.

1. *Average speed to fuel consumption*:

Driving the vehicle on average speed significantly decrease the fuel consumption. Results showed that if vehicle average speed is ~ 55 mph then its fuel consumption is at optimal level [12].

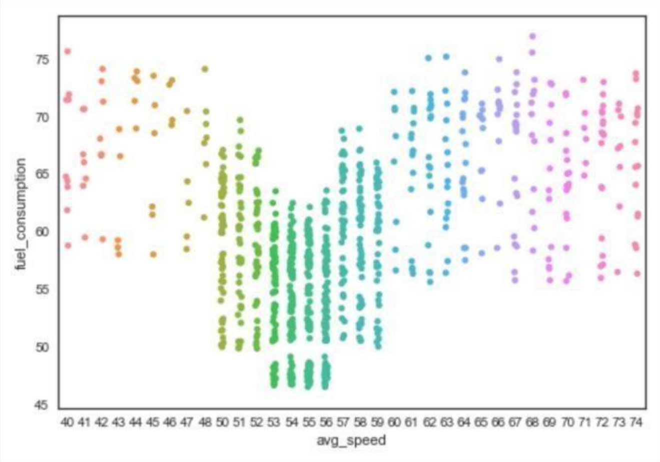


Fig. 15. Average speed to fuel consumption correlation plot

2. *Idle wait time to fuel consumption:* If the idle waiting time of fuel is more, fuel consumption also increases.

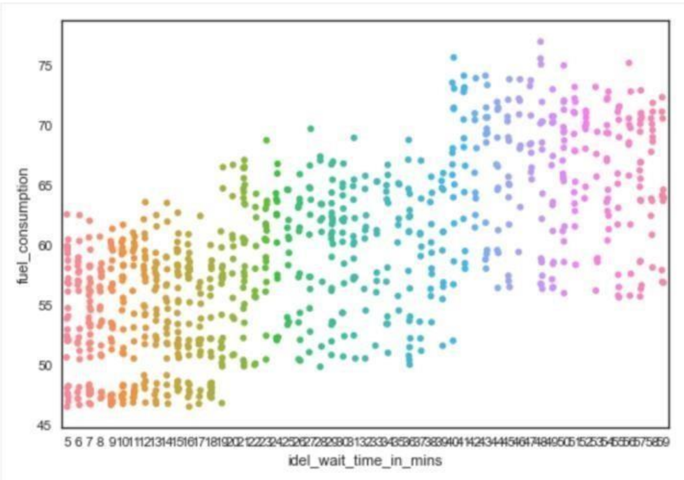


Fig. 16. Idle wait time to fuel consumption correlation plot

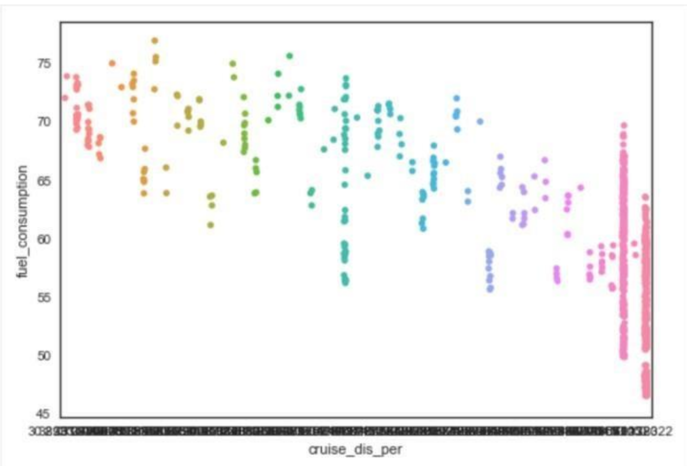


Fig. 17. Distance covered with cruise control to fuel consumption

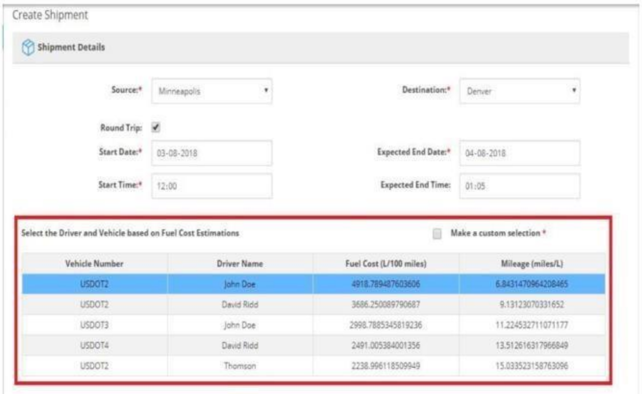
3. *Distance covered with cruise control to fuel consumption*

More the distance covered with cruise control at recommended speed i.e. 55 mph has the best fuel consumption. Anything less or more tends to have more fuel consumption. correlation plot

Experimentation also found correlation between Truck Load to fuel consumption.

Based on the study, two level recommendation system was developed and integrated with Fleet solution.

1. Truck and Driver recommendation: This module provides best five truck and driver combinations predicting highest mileage or low fuel consumption based historical data of trucks & drivers performing on the same route. This is recommended at the time of shipment creation to the admin.



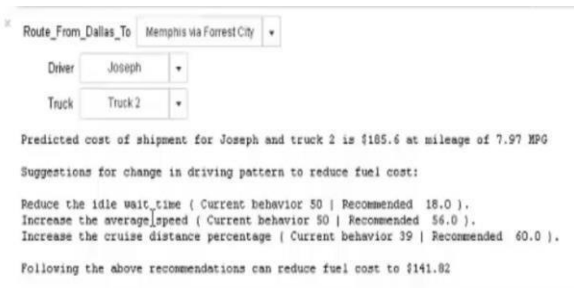
Vehicle Number	Driver Name	Fuel Cost (L/100 miles)	Mileage (miles/L)
USDOT2	John Doe	4918.789487603606	6.8431470964208465
USDOT2	David Ridd	3686.250089790687	9.13123070331652
USDOT3	John Doe	2998.7885345819236	11.224532711071177
USDOT4	David Ridd	2491.005384001356	13.512616317966849
USDOT2	Thomson	2238.996118509949	15.033523158763096

Fig. 18. Top 5 truck-driver combinations providing best mileage or low fuel consumption suggested by Fuel Prediction module

2. Driving pattern recommendation: For any reasons admin wants to select some other truck driver combination then system recommends the driving pattern recommendation to the driver to achieve better mileage. It considers the historical data for given driver on selected route. Machine learning SVR (Support Vector Regression) model was used to predict the result. Following example shows the same. For route

Recommended 18.0)

2. Increase average speed (Current 50 | Recommended 56.0)[13]
3. Increase cruise distance percentage (Current 19 | Recommended 60.0)



mileage 7.97 MPG. Its recommends the driving pattern

Memphis via Forrest City with combination of Driver Joseph and Truck2. It predicts the cost of shipment is $185.6 with to reduce fuel cost by suggesting to: 1. Reduce Idle wait time (Current 50 |

Fig. 19. Driver driving pattern recommendation for better mileage

More studies are in progress to collect data and to find correlation of fuel consumption with more parameters like weather conditions [14], route conditions, shipment types.

C. Challenge C: Material Damage and Theft Solution:

Fleet Management System monitors:
Health of the fleet (Fuel, Route, Location & Timestamp),
Geo location. Vehicle dashboard displays

- instantaneous monitoring of location & timestamp details,
- direction: Inward, Outward, Round Trip direction of fleet.

Driver Centric Monitoring-

- Wrong Direction: Notify operator whether driver is moving in wrong direction,
- Idle Time: Notify operator if driver is exceeding idle time. Idle time can be configured,
- Over speeding: Notify operator if driver is over speeding
- Alerts/ Notifications - Container internal parameters (Door Open(close/open),
  Temperature, Human Presence, Humidity,
  Light Intensity)

Fig. 20. Vehicle Monitoring Dahsboard

D. Challenge D: Material Damage and Identifying Fake vs Genuine Customer Insurance Claims Solution:

Fleet Management System provides continuous monitoring of internal environmental parameters. This helps admins to take immediate actions when an essential parameter like temperate goes out of range. Various shipment reports of container internal parameters help fleet companies to identify false vs genuine claims and save huge cost of false penalties for material damage.

Fig. 21. ContaiContainer internal parameters (represented in graphs & tabular format), Temperature, Humidity, Light Intensity

V. HARDWARE AND SOFTWARE USED

Hardware
Raspberry Pi 3 Model B 1.2 GHz 64-bit quad-core ARM Cortex A53 CPU – 2 numbers
Rhydolabz sim900A (GSM/GPRS/GPS) Shield
Temperature and Humidity sensor (DHT11)
Reed Switch sensor
LDR sensor
PIR motion sensor
Multybyte Hdmi To Vga With Audio
Vehicle Chassis
LogTech Camera
OBD-II Parameter

- IBM Cloud
- Bluemix, Watson IoT, CloudantDB, Conversation APIs, Speech to Text and Text to Speech APIs, Alchemy APIs for Headlines, Bluemix TWC service APIs for Weather, Google APIs for Traffic, Visual recognition APIs
- Heruku Server
- Scikit Learn, OpenCV, Tensor Flow, and various other computer vision and deep learning libs
- PythonNode.js and UI Technologies
- http, websockets and MQTT protocols

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