Predicting Grade of Road for Autonomous Vehicles Using Supervised Deep Learning

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***Abstract*— A novel deep learning approach towards estimating the grade of the road ahead of the vehicle through vision is presented in this paper. We have used Inertial Measurement Unit (IMU) pitch values and also Global Positioning System (GPS) altitude values to estimate road grade. Image segmentation has been employed to check if the model performs better when trained specifically on the edges. Convolutional Neural Network (CNN) architecture has been used to predict the grade of the road. We have successfully implemented the model in real time to evaluate the grade resulting in considerable performance. With this paper we aim to give an insight into how a vehicle will change its power distribution if it has the knowledge about the upcoming grade. This will help in improving the fuel economy, ride safety and comfort to quite an extent.**

***Index Terms*— Deep Learning, Autonomous Vehicles, Supervised Learning, Sensor Prediction, Neural Network, Grade Estimation, Computer Vision, Slope prediction**

I. INTRODUCTION

Road geometry influences the road safety as well as the power dynamics of the vehicle traversing through the road. One of the aspects of road geometry is the grade of road. The Grade of the road is a measure of its inclination or slope. The amount of grade indicates the inclination or slope of the road from the horizontal. For example, a perfectly flat and level road will have a grade Zero (however, for practical purposes, to allow sufficient drainage, minimum grade is kept as 1). Grade detection is a very useful aspect of autonomous vehicle applications and mobile robot systems. Knowledge of the change in the elevation of the road ahead of an autonomous vehicle will help it to distribute the power accordingly beforehand. This approach can be applied to vehicles such as mars rovers, self driving cars, off-road vehicles and other Advanced Driver Assistance Systems (ADAS).

Generally, Inertial Measurement Units (IMUs) or tilt sensors are used in autonomous vehicles to calculate the inclination/declination of a vehicle, often along with Global Positioning System (GPS) sensors, which obtain the current location and altitude data of the vehicle on a global scale. These sensors provide only the real time data and no information about the upcoming grade of road is given, which is a significant drawback. Unfortunately, very little research has taken place to accurately determine the grade of road beforehand, without being on the inclined surface itself.

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We have implemented a deep learning based algorithm for predicting the grade of road in advance, on which the vehicle has to traverse on, so that the power-distribution can be adjusted accordingly. This will minimize the losses incurred in the current techniques, where the power-distribution is altered after the vehicle is at a particular grade.

The implementation of grade detection in advance will also improve the ride comfort and road safety. The motivation behind the idea of grade detection in advance was from the implementation of Active suspension system used by Mercedes-Benz by M. Becker et al [10].

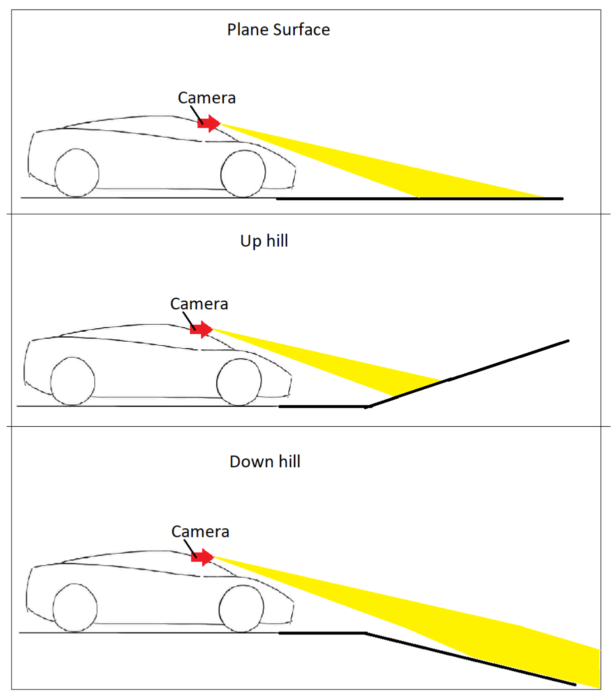

Fig. 1: Perception of varied road contours

The dash-camera on a car records images with different contours, when facing plane surfaces with different road-grades. The above images shows field-of-vision on a sharp-incline road, flat road and a sharp-decline road respectively.

As shown in Figure 1, a camera mounted on the hood or dashboard of the car has long-range sensing capabilities as opposed to an IMU or GPS sensor. It can detect varied contours that the vehicle will travel upon, such as steep inclines, declines, or off-road obstacles. By combining the long-range capabilities of a camera with the instantaneous grade detection of GPS and IMU sensors, we can develop a deep learning architecture which will alter the vehicle dynamics as per corresponding future grade data, benefiting the passenger safety as well as power consumption of the vehicle.

II. LITERATURE REVIEW

The approach to detect grade in advance can be handled in a number of ways, as previously demonstrated by numerous research teams. They have made use of Inertial measurement sensors, Global positioning system, LIDAR (Light detection and ranging technique), Ultrasonic sensors etc. Among these varying sources of input, different techniques exist which modify the data in several ways to obtain the desired output. These techniques have acquired the same goal that we are working on yet their approach towards the task is quite different.

Per Sahlholm et al [13] in their paper have used standard High Duty Vehicle sensors and GPS to create a road map data. They then carried out data fusion via spatial sampling. Extended Kalman Filter was applied to carry out road grade estimation . Combined road grade estimate from six measurements of three different vehicles was compared to independent reference road data. The noise covariance matrix was assumed to be diagonal at all times, which is not always the case. Also, the Extended Kalman filter cannot predict any gearshifts or brakes applied. To compensate for this, whenever brakes were applied, the error increased (as the process noise was increased) and the weight of that particular observation was decreased while overlapping the data.

In their paper Jens Jauch et al [14] have used different filters such as Mahogany filter, Madgwick filter, Complimentary filter and Orientation filter to fuse raw data from the gyroscope, accelerometer and magnetometer to estimate the orientation of the sensor relative to the earth's surface. The methods are evaluated against a high resolution road grade data prepared using an aircraft equipped with LIDAR sensor. The measurements obtained after applying the filters (mainly orientation filter) give the pitch angle . Pitch angle is the angle created by the vehicle's longitudinal axis and the horizontal. A low pass filter can then be applied to calculate the grade of the road. This approach eliminates the need of a complex model and works even when there is no GPS signal available. Data from numerous vehicles is generated and compared to LIDAR data. With the increase in number of vehicles the road grade of the whole infrastructure can be precisely estimated and a high resolution digital map can be created and kept updated almost in real-time.

The use of GPS to calculate the grade of the road can be seen in [12] by Hong S. Bae et al. They present two different techniques to estimate the grade of the road using GPS. One of the techniques involves using two GPS antennae on the roof of the car longitudinally with a fixed baseline and directly measuring the attitude of the vehicle in the pitch plane using the angle of this baseline. Since the GPS is mounted on the receiver, the measurements correspond to the sum of the pitch angle and road grade . The low frequency part of the signal can be associated with the road grade since road grade does not change as rapidly as the pitch angle does.

The other technique involves using a single GPS receiver and calculating the grade of the road based on the difference in the readings. This can be thought of as the ratio of vertical velocity and the horizontal velocity. Parameters such as the engine torque,mass of the vehicle air drag etc have been taken into account and the use of low pass filters such as Butterworth low pass Filter has been done to remove any unmoderated high frequencies.

Both the approaches have been compared and its been found that though both these techniques give similar results , a single GPS antenna is more robust than two GPS antennae.

In a text titled Vehicle Mass and Road Grade Estimation Using Kalman Filter[15], the author Erik Jonsson Holm has discussed the importance of the mass of the vehicle, air drag, the engine torque, friction etc in deciding the adjustment in power distribution of the vehicle on different grades. The approach is similar to the above mentioned approaches and uses an extended Kalman filter to estimate the topology of the road. Two estimators were developed; one estimates both vehicle mass and road grade and the other estimates only vehicle mass using an inclination sensor as an additional measurement.The text highlights advantages such as improving fuel economy and cost effectiveness of the method over hardware solutions.

2-Dimensional (2-D) cameras are some of the more popular hardwares used for related purposes in automobiles, due to their presence in everyday scenarios. Some work has been done in the area of detection of non-flat roads using a local descriptor [3], which utilizes a technique for plane surface detection using SLIC(Simple linear iterative clustering). Another technique which uses a known-shape planar object for measuring another vehicles orientation is described in [7]. These techniques have a disadvantage, which can be expressed as a lack of dynamic reference and techniques that are less effective than a Stereo-Camera at accurately determining the depth component of a scene.

Stereo-Cameras are, perhaps, the most efficient type of input hardware for our project. A few previous studies indicate potential for application in detection of components of the road which can be done more efficiently than other hardware by using 3D space based algorithm for the disparity algorithm [6]. This paper goes in-depth, with regards to generating elevation maps that can be potentially utilized for generating slope data from dataset. Another potentially powerful technique for estimating upward and downward slope is described in [8]. In this paper, using a stereo vision the surface is detected and the disparity image is divided into regions which helps to extract the surface profile piecewise by providing us the surface depth and direction information in the sub-V-disparity map.

For certain applications, a hybrid combination of 3-D stereo-cameras for training a network, and implementation on 2-D camera can be feasible [2]. Such a technique could effectively eliminate the short range issue of Stereo camera, which can only handle ten to twelve meters of distance (which can be ineffective for our project due to the speed of the vehicle).

Another novel technique utilizes a Light Field Camera which is a device that extracts angular information as well as spatial coordinates of a point on an image. This method, described in [1], essentially uses the spatial as well as angular information of the image obtained to determine the flat surfaces in a dataset. This technique might be discouraged in certain scenarios, due to the additional cost of this Camera and the complexity of the problem.

In addition to choosing a proper source of input for the algorithm, it is a requirement that the data set consisting of multiple sensor information must be properly synchronized, in order to correctly convey the relevant information to the system. If not done properly, with a large enough error rate the algorithm risks malfunction and faulty learning. Thus, for accurate learning and prediction characteristics, we require a dataset that successfully synchronizes its sensor data with minimum error. [11]

III. Problem statement

Currently, the autonomous vehicles do not have any information about the grade of the road ahead of them. The vehicle changes its power dynamics as the IMU sensor and GPS sensor readings change or through the Adaptive Cruise Control. If the vehicle can gather information about the grade in advance, and distribute power accordingly, it will result in a more comfortable, safer and efficient experience.

Hence, our concept is to design an algorithm, that can detect the change in the inclination or declination of the road ahead based on the input received to the camera attached to the vehicle. However, our neural network has been trained in urban areas and that limits its performance currently only on highways and similar on-road trajectories. Even though GPS and IMU sensors have been used before for grade calculation, using a camera for predicting grade by employing a deep learning neural network has never been attempted before.

IV. Dataset

The Dataset has been acquired from L. Fridman et al, "Automated synchronization of driving data using vibration and steering events [11] . This setup was supplemented with input from a millisecond-clock to help synchronize the devices. In order to achieve an accurate prediction of the slope of the road by reading future IMU and GPS velocity data, cross correlating them with the image input data from a front camera (Logitech HD Pro WebCam C920), we require a method to synchronize the various sensor data we obtain in a manner where the delay between the said sensor data outputs is as low as possible.

The video frame rate is 30 frames per second (fps). Hence it generates 30 images for each second on parsing. From this dataset we have just used the IMU pitch(meters) and GPS altitude(meters) and the GPS velocity(meter/second) . All other data has been not used by us because the approach that we have adopted requires only these parameters. IMU pitch gives the pitch angle of the vehicle which is nothing but the angle between the vehicle's longitudinal axis and the horizontal. For simplicity, we have assumed that the pitch

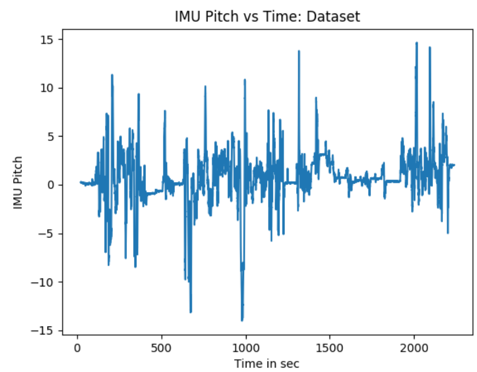

Fig. 2: Dataset: IMU Pitch plotted against time duration

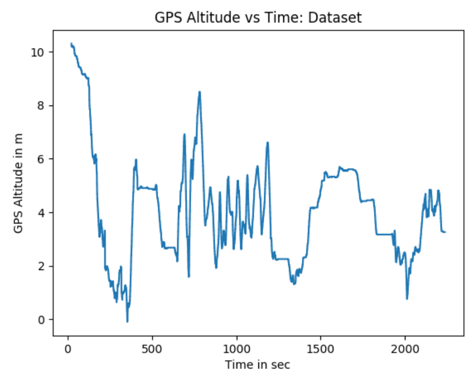

Fig. 3: Dataset: GPS Altitude plotted against time duration

IMU pitch and GPS Altitude data tracked during the dataset, is plotted in fig(2) and fig(3) respectively. The IMU pitch data follows a zero-centered nature while the Altitude shows us the car-altitude in an absolute world-frame (which can be converted to local frame).This sensor data can collectively be used to predict the absolute road-grade.

angle represents the grade of the road. The GPS altitude reading tells the height of the vehicle from sea level at that particular point. The Velocity recorded by the GPS is taken as the vehicle's velocity. Currently, the model might be flawed where incorrect IMU and GPS measurements occur but the concept and the approach is justified and with a few enhancements such as using low pass filters on IMU pitch angle and GPS altitude readings, the system can be made more robust.

A. Video Parsing

The given dataset consists of a variety of sensor data such as GPS, IMU, sound, etc. along with a 36-minute video consisting of the entire ride along the defined track. The sensor data for the given ride is provided at certain timestamps in the video, corresponding to individual frames of the video (In our case, the video is shot at 30 frames per second). In order to categorize this data, we parse the video based on the timestamps given in the sensor data, obtaining a set of images each with their corresponding sensor data.

B. Image segmentation

The original image (1280p x 720p), converted to a square image of resolution (720p x 720p) was used initially for the Neural Network as it is easier to operate on CNN using squared images. We also used Image Segmentation method where our input image is thresholded to mask unwanted items in the background, and then segmented to retain only the edges of the road, obtained with the help of lane markers present in the dataset.

C. IMU/GPS data parsing

IMU pitch and GPS altitude are the values we have obtained in the Global frame of reference, whereas to make our neural network model generic we had to convert the data to local frame. Considering the dataset the Vehicle starts and ends at the same position. So we can take the starting position as our frame of reference.

After obtaining the corresponding input images for matching sensor data, we must now consider the complete picture of the input data given to our Neural Network. Since our algorithm will predict the future slope (i.e the road gradient of the road section displayed in the image) we need to match it with the proper data to portray it as a prediction for validation. Since the GPS and IMU data corresponds to the current position of the vehicle, we average the data of 30 frames (1 second) ahead of the current frame of the vehicle and pair it up with the respective frame. This method will help to obtain proper input data for the architecture.

V. Approach

Our approach can be explained in the following sections:

A. Data pre-processing

After experimenting with the neural network, input formats, and background research on relevant topics, we determined that original dataset worked better than the segmented variants for our deep learning architecture. A segmented version of the image filters out the background in such a way that it leaves only the edges of lane-markers on the road. The segmented version of images also leaks a lot of relevant features about the environment which helps the neural network to predict the grade.

We have experimented with both these formats of input image data and found that the model is well trained with less RMSE (Root Mean Square Error) for original image compared to segmented image.

B. Data Processing

1) Data smoothening Filters: The Inertial Measurement Unit is very efficient at obtaining the angle of the positioned vehicle, which extends to depicting the resultant grade of the road. However, IMU readings are often noisy, and heavily affected due to the high frequency noise incorporated due to variations in the road structure. To alleviate this problem, we test and apply filters to the data to help it "smooth-out" the readings, eliminating the high-frequency variations and retaining the low-frequency pitch data corresponding to the road grade [12]. Some of the filters that efficiently perform this task are the Moving Average filter and the SavitzkyGolay filter.

   a) *Moving-Average filter*: The Moving Average filter is a widely used technique for detecting trends

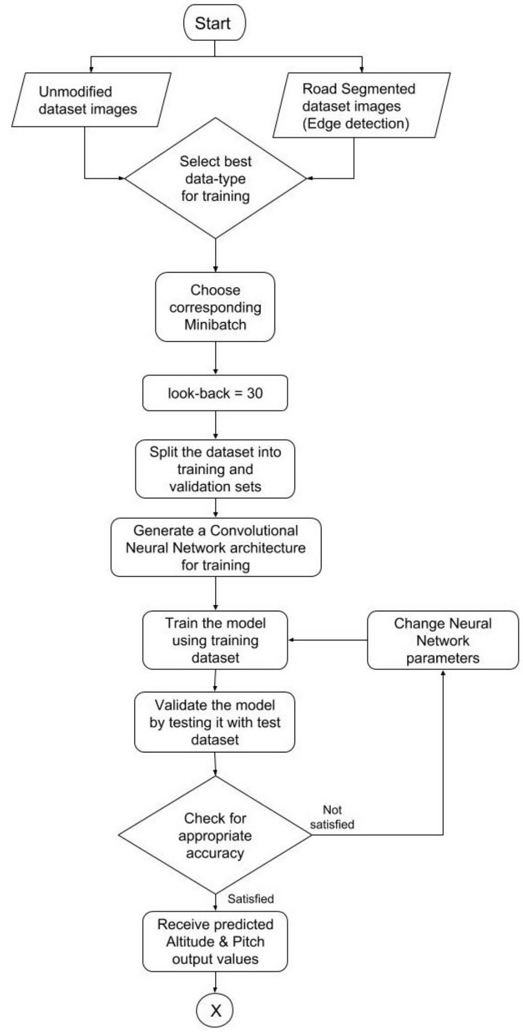

Fig. 4: Flow chart

Primarily, we choose between segmented and unsegmented dataset for ideal input format. Training and validation sets are then separated, with a lookback of 30 frames to obtain input image for the next second (due to 30 fps) for prediction and validation. The neural network architecture is then tested and refined till we obtain satisfactory prediction output values.

Fig. 5: Original Image

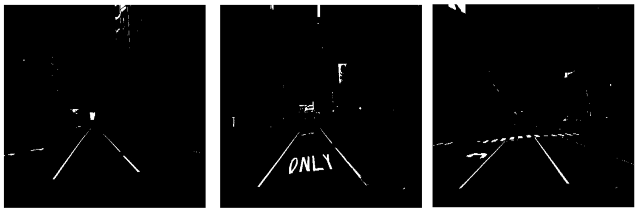

Fig. 6: Road Segmentation

The original input images and their segmented versions are shown in fig(5) and fig(6) respectively. Segmentation attempts to preserve crucial information needed for our model's prediction, while discarding the unnecessary information. Both the input dataset versions are tested with different models to determine the input which gives the best performance.

in the sensor data, without distorting the input information to a large degree. This filter smooths the data by averaging a certain amount of data in previous and next time-steps, creating a smooth curve from distorted information. A downside of this filter is that by doing so, it eliminates a corresponding amount of data from the start and end of the data. Thus a bigger filter size interferes with the dataset dimension. Since the required smoothing was acquired at higher settings, to eliminate dataset loss for training our network, we chose not to adopt this filter.

b) *Savitzky-Golay filter*: Savitzky-Golay filter is popularly known as the Digital Polynomial Smoothing filter. As opposed to averaging a batch-sized data, this filter undertakes polynomial fitting through a segment of data, or "frames", effectively smoothing a large range of data without causing data loss and retaining the overall shape of the curves. This filter is especially useful due to the availability of hyper-parameters such as the frame-size and polynomial order, which can be tweaked for best results through trial and error. We applied this filter with a batch-size of 91 for the best smoothing results. This filter enables us to interpret the noisy pitch data as a smooth, grade/slope component corresponding to the road geometry.

2) Look back: The image predicts the value which will come in the near-future time step and therefore it is necessary to process the data accordingly so that the model gets trained based on the values with reference to image. Therefore, we have introduced 'look-back', which is the number of previous time steps to use as input variables to predict the next time period. Assuming the velocity constrains in the Urban area and based on the distance the car will be traveling, we have considered a look back of 60 in our model. That means the images will be trained with the value which is 60 frames ahead or 2 seconds ahead (as per 30fps video parsing). Hence, look back is an important step in our data processing.

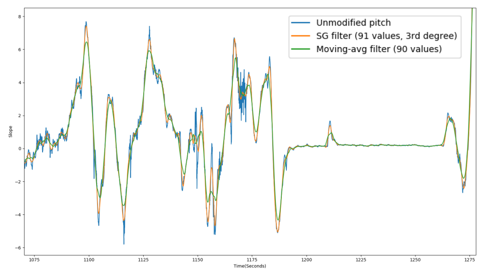

Fig. 7: Comparison: Moving average filter and Savitzky-Golay Filter

IMU Pitch data is highly erratic, causing vaiation due to road-bumps and obstacles. The Savitzky-Golay filter and Moving-Average filter were tested for smoothing out the high-frequency readings, while preserving the low-frequency data corresponding closely to the road-grade variations. The Savitzky-Golay filter proved to provide greater variation and freedom in filtering parameters, making it easier to fine-tune the filter to track the road-grade more closely.

3) Dividing dataset : The dataset was divided into three sections. From 66382 images we have considered to train the model on images from frame 10000 to frame 50000 (40000 images) out of which 67% of images were considered for training (26800 images) and 33% of images were considered for validation (13200 images). The third section was chosen as test data for which we have considered images from frame 55000 to frame 60000, which were used for real time implementation as discussed in the Application section.

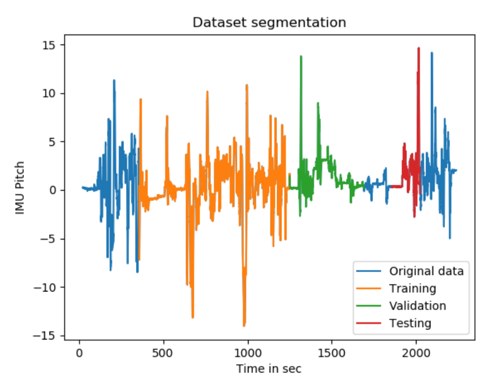

Fig. 8: Data Segmentation for IMU Pitch

C. Data post-processing

- Grade Calculation
  - Based on IMU Pitch:

$$Slope = PredictedPitch$$

  - Based on GPS Altitude:

$$Slope = \frac{PredictedAltitude - CurrentAltitude}{CurrentVelocityxTime}$$

Time = 1 second for calculating the slope in between 30 frames. (As per the dataset the velocity is constant for 1 second taken at 30fps)

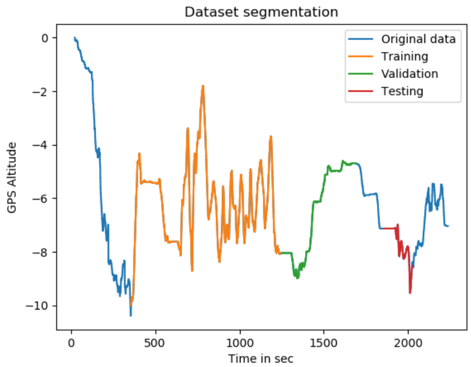

Fig. 9: Data Segmentation for GPS Altitude

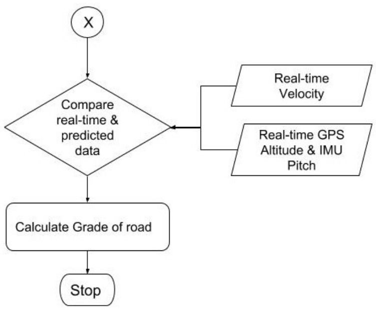

Fig. 10: Grade Calculation

VI. Architecture and Training

In order to optimize the algorithm we had to come up with a model which could process input images based on regression outputs. We have used Convolutional Neural Networks (CNN) with dense layers in our model. The architecture consists of series of Convolution 2D layers and max pooling applied to the image. In our architecture we have applied two consecutive Convolution2D layers 32 filters of kernel size (3,3) and stride 1, adding a max pooling layer of kernel size (2,2) and stride 2, followed by 2 more Convolution2D layers (64 filters of kernel size (3,3), stride 1) and then a max pooling layer, finally adding a Convolution layer (128 filters of kernel size (3,3)). We chose max pooling as it gives better results as compared to average pooling.

We have also applied a dropout 15% between every Convolution2D layer in order to decrease the over-fitting of the data. Based on a trial and error we choose the dropout of 15%, with which we achieved the best results. Ending with 3 fully connected layers connected to 3 dense layers of 1024 neurons, 512 neurons and 2 neurons (because we have 2 classes - IMU Pitch and GPS Altitude) respectively.

A regular network is too computationally expensive as compared to CNN, when operating on images. The CNN always considers the input as an image. Furthermore , the neurons of CNN are arranged 3 dimensionally i.e., (width,height,depth) which for our model is (3,36,36).

We have trained the model using ADAM optimizer and loss is computed by mean squared error. Furthermore, the data has been trained using a batch size of 150 for 10 epochs.

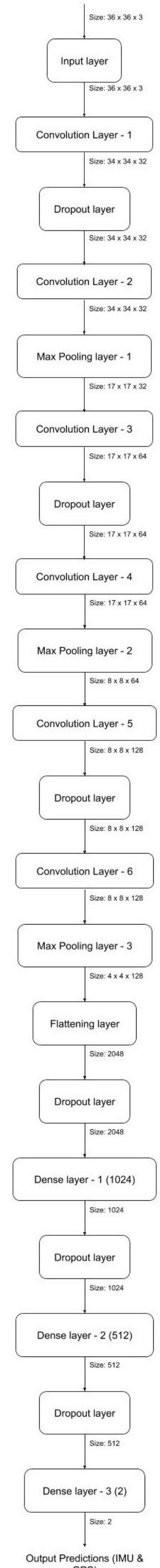

Fig. 11: Neural Network Model

VII. RESULTS

The model performed quite well by predicting the grade based on both the methods explained above. The training and validation loss decreased with increase in the number of epochs. Root mean square error (RMSE) after 10 epoch are:

- For predicting IMU Pitch: Training: 0.40 RMSE, Validation: 2.25 RMSE
- For predicting GPS Altitude: Training: 0.51 RMSE, Validation: 1.85 RMSE

The model gave an accuracy of 99.19% on training data and an accuracy of 98.77% on the test data. While testing in real-time, the data associated with the GPS gave huge errors. The GPS has horizontal accuracy of about 10 meters and vertical accuracy of about 15m. The GPS alone should not be used for such tasks for the sole purpose of their lack of precision and various limitations associated with it. We recommend that GPS data should always be used through data fusion with other sensors and filtering. Comparing the results obtained for both the methods we can infer that IMU pitch provided us with better grade values as compared to GPS Altitude.

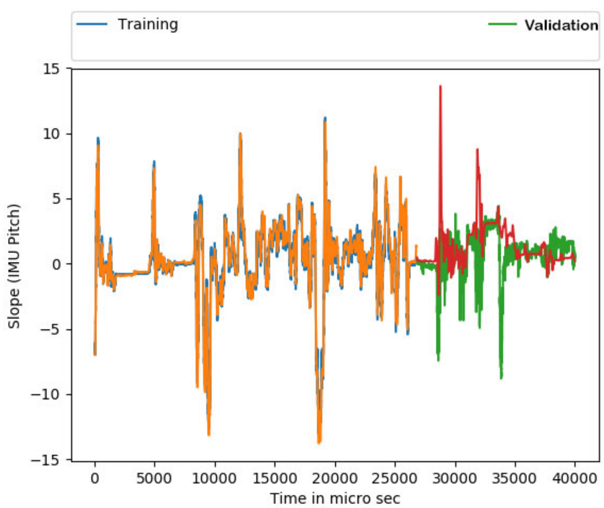

Fig. 12: Result: Slope (IMU pitch) vs Image frames (30 fps)

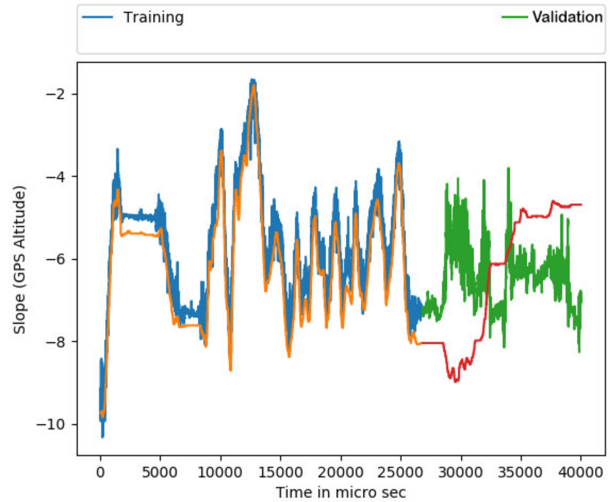

Fig. 13: Result: Slope (GPS Altitude) vs Image frames (30 fps)

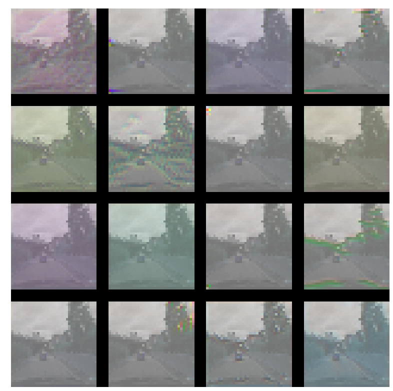

Fig. 14: CNN Layer 1

As seen in Fig 14. The images are processed by the CNN layer by layer in order to extract relevant information. The figure above is the visualization of CNN layer 1.

A. *Visualization of CNN Layers*

Convolutional layer 1 is shown in the figure

VIII. APPLICATIONS AND FUTURE SCOPE

Modification of vehicles for automated driving capabilities is one of the most widely researched topic in the current scenario. New techniques are constantly being searched for, to make autonomous vehicles act more like a human driver such as using inherent intuition to adapt to the circumstances of the road.

We aim to enable the application of camera-based computer vision with deep learning to predict the gradient of the road, in order to predict circumstances crucial to the control of the vehicle. A future application of our project could be the integration of proportional acceleration control with respect to the detected road grade, in order to achieve smooth and flawless power transition. This implementation could be very useful for automobiles driven in hilly areas, and can even contribute to the safety of vehicles when being driven autonomously in steep hilly regions, with power regulation and less overshoots.

As far as the neural network is concerned, implementation of Long short-term memory (LSTM) network along with CNN could help boost the performance of the model as the LSTM is capable of retaining memory of the previous results, which might help in a better estimation of the change in grade.

In addition, we also aim to spark interest in a trend for futuristic sensor data prediction based on vision, in a manner that can help autonomous automobiles understand and avoid less favorable scenarios, increasing safety even beyond regular human capabilities which will contribute in a meaningful manner to the predictive autonomous vehicle system capabilities.

A. Implementation

The trained neural-network will produce a Json file which will maintain the structure of the Neural Network, and an h5 file which will preserve the weights of the model. Using this model file, we can recreate the model and test foreign inputs and get the resulting data. With the help of this data, we generated an inferred road grade with the help of visuals to predict when the vehicle should slow down or speed up, depending on the predicted road grade value as shown in the figures.

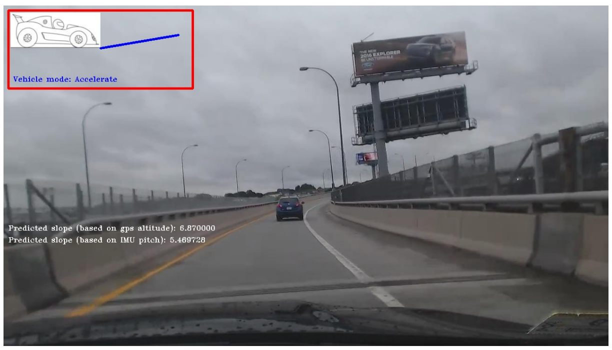

Fig. 15: Upwards Slope

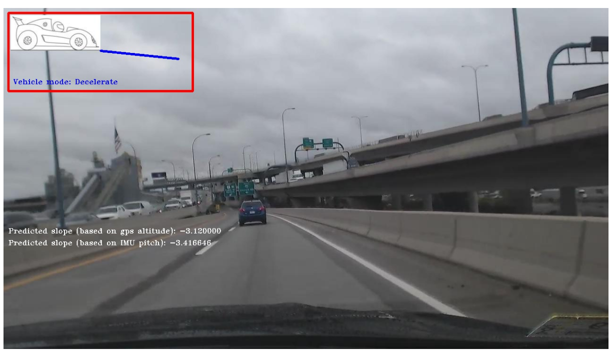

Fig. 16: Downwards Slope

As seen in Figure 15 and Figure 16, the vehicle can recieve information whether there is an upward slope or downward slope ahead and adjust accordingly. This would result in increased efficiency and comfort.

With the help of this video example, we hope to give an vivid feedback of the output of the system as well as provide indication for control of vehicle to the user. This could also be applied in an automated system for further application.

IX. CONCLUSION

This paper presents a novel deep learning approach towards estimating the grade of the road ahead of the vehicle through vision. While most of the existing research is focused on obtaining a real-time, accurate road grade calculation, very little research has been done regarding determining the road grade using vision, reducing dependency on additional on-board sensor kits by adopting a camera for the purpose. Deep learning brings this possibility to fruition as we devised a method to estimate the road grade with a vision-based prediction.

Two different techniques have been used for this grade estimation. The first methods uses the Inertial Measurement Unit (IMU) pitch readings for estimating the grade. The pitch readings correspond to the pitch angle (the angle between the longitudinal axis of the vehicle and the horizontal) which approximates the grade of the road. The other method is based on using Global positioning System (GPS). Altitude readings at two varying instances of time can be compared, the resultant extrapolation providing angular data corresponding to the vehicular position with respect to the road on a local frame. This data is thus inferred as the road grade by geometric calculations.

These values are then used a labeled data corresponding to specific images and the images have been fed to a Convolutional Neural Network (CNN) as inputs. With enough training data, the CNN was able to accurately predict the grade of the visual road-feed. A Savitzky-Golay filter is used to smoothen the data by eradicating sudden spikes, maintaining the low-frequency data corresponding to the road grade. Performances of all these methods have been evaluated and compared in this paper.

This paper aims to merge the possibilities of vision-based Deep Learning with accurate sensors, potentially a step towards creating a better basis for autonomous vehicle power-regulation and increased passenger safety . The predictive and adaptive power-regulation would also help in improving fuel efficiency, and subsequently driver satisfaction.

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