Project Proposal

Enhancing Railway Safety using Computer Vision and Cloud Based Technologies

Tech Wizards

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1. Introduction

Railway transportation stands out as a highly efficient mode of land transport. Train accidents still exist even though significant improvements in safety procedures and technology. Considering this, the goal of our research project is to develop and implement an innovative web application using advanced computer vision and cloud-based technologies to address significant issues faced by locomotive pilots.

Our project focuses on making train journeys even safer by using computer vision and cloud technologies. We want to create a special system that gives locomotive pilots the most current details about where they are and what the weather is like on their route, including carefully tracking areas prone to flooding due to heavy rain or landslide risks along the railway tracks. The application we are creating will deliver timely updates on various critical factors. For instance, it will notify locomotive pilots about precipitation levels, ensuring they are aware of rain or any other weather-related challenges like landslides based on rainfall. Moreover, the system will pay special attention to visibility conditions, particularly in situations like fog or mist, providing real-time insights to assist drivers in navigating safely. Additionally, wind speed updates will be integrated, enabling drivers to adapt to varying conditions promptly. Our project focuses on improving railway safety by providing locomotive pilots with location and crucial weather updates. This empowers them to make informed decisions, ensuring a safer and more reliable travel experience for passengers.

In our project, we are implementing advanced object detection algorithms designed to accurately identify both stationary and moving objects on railway tracks, with a specific emphasis on detecting obstacles like wild animals, large vehicles, and other potential hazards. This involves identifying animals such as bulls and elephants in the areas where the train is moving along the railway track. Our primary focus is on ensuring exact identification with high accuracy and reliability, even in diverse environmental and lighting conditions. By prioritizing safety, we aim to enhance railway operations and minimize risks associated with various obstacles on the tracks.

Our project focuses on enhancing railway safety through the development of an efficient system capable of rapidly processing live camera feeds and real-time data streams. The primary goal is to minimize latency and optimize the processing flow to provide locomotive pilots with instantaneous feedback regarding detected objects, their location, and prevailing weather conditions. By creating such a system, we aim to significantly improve the responsiveness and overall safety of railway operations.

We're developing a web application for locomotive pilots that shows real-time information about detected objects, weather, location, and potential hazards. It will have a simple and interactive user interface, and the system alerts through voice alerts. This web application aims to make railways safer and more efficient.

2. Background and Motivation

The authors of the article discussed since the track is easily distinguished as a distinct converging edge, edge detection is the recommended approach for track detection. Mexican hat filtering was used to filter the image, and then Canny edge detection was applied. The prominent lines were then found using Hough's line transform. If there is just one track, the lines that represent the left and right halves of the track can be merged by arranging them according to slope. Sorting is carried out considering both the slope and the distance from the origin in cases where there are multiple tracks. It was noted, though, that although this method performs admirably for the main track, obstacles like shadows and slopes make it difficult for it to identify distant tracks.[1].

At 1024 × 1024 pixels, every image in the dataset has a high resolution. These photos were shot in open railway tracks as well as rail yards under a variety of environmental circumstances. The scenes' multiple objects, obstacles, and background elements make automated detection and recognition tasks difficult. Nonetheless, during field operations, the suggested approach has shown to be efficient and appropriate for real-world situations. With only approximately 5% of frames containing a signal, the FR Sign dataset suffers from severe class imbalance, much like many other object detection tasks in the transportation domain. [2].

We examine each frame's fourth component, which includes important track information, to identify the railway track. The fourth component is what we use in this study to identify the railway track. To represent the tracks, their features are separated from this component and superimposed on the frame. All frames undergo this uniform procedure, which guarantees accurate track identification. Finding items (obstacles) on the railway track comes next, following the detection and visualization of the track. The deep network for obstacle recognition receives input from the decomposed components, which carry important information about obstacles. It is observed that the component contains important information about obstacles on the railway tracks through analysis of each component in each frame. [5].

The experiment method uses 8500 photos of railroad scenes from the RailSem19 dataset, which spans thirty-five categories. Each image has a resolution of 1024 x 1920. It includes sceneries with varying weather, lighting, and seasons as well as scenes with intricate level crossings and other scenes with embedded railroad platforms. This dataset presents a difficult image segmentation challenge. Except for the rail lines, which were labeled as the foreground and other objects in the image were tagged as the background, we employed preprocessing on the dataset images. We chose six thousand photographs at random for the training phase, and 2500 images for the validation process [3].

The frame contains objects, and any items with red pixels are recognized as being red objects. the Hough Using template matching, the items are categorized according to shape and matched to the database's standard data set. binary picture the correlation coefficient method is used to compare two photographs. The warning message is delivered to the driver via voice output [4].

We employed a convolutional neural network for detection. Using CNN, the set of classes was learned. The convolutional neural network model passes the input image that we take with the camera to the convolution layer. The pooling layer combined the photos. By lowering the dimensions and passing into the fully linked layer, the pooling layer merges the pictures in the convolution layer. Each neuron in the output layer is coupled to the neurons in the fully connected layer. Dark net software was used to store the files. CNN was used to learn the photos, after which they were matched to the sets stored animals. The categorization procedure is comparable to the multilayer perceptron process that we use. With a training rate of 0.3, the layer trains the neurons. The weights supplied to the output layer from the neuron and attached to it are used to determine the neuron's output. As more hidden layers are applied, the faults in the layers may get worse. A momentum of 0.2 was used during the training to conduct the alterations [6].

We developed an original approach to create a user-friendly driver monitoring system with Graphical User Interface based on the issues raised by the background study. The key characteristics of our suggested models are. A good GUI that guides users to the system. The user's ability to add more users to the system for vehicle usage with the help of machine learning, it can detect drunkenness and drowsiness. The vehicle engine will only start if the driver is in a sober state. It will monitor the driver intelligently from the time the car is turned on until it has reached its destination [7].

In the context of deep learning-based object detection methods, there are two main categories: two-stage algorithms and single-stage methods. Two-stage algorithms, exemplified by the R-CNN series, generate region proposals, extract image features, and then predict classifications, resulting in better detection accuracy. However, their longer running time makes them unsuitable for real-time locomotive operation applications, where the efficiency of single-stage methods becomes crucial. The experiment focused on detecting railway pedestrians using the DLSLRP dataset. Results indicate that our method achieves high detection speed and precision in recognizing railway pedestrians within a range of 1.5 kilometers. [8].

The former employs multi-scale feature layers for object detection and blends the YOLO grid concept with the anchor mechanism of Faster R-CNN. The latter does feature extraction and regression analysis for each position in the full image using multi-scale feature mapping. The number of SSD's parameters is lower than that of YOLOv4 since all of SSD's feature data originates from the bottom layer of the feature pyramid [9].

This cloud computing model uses a remote cloud operation. Through web browsers or remote access, users can access applications and software over the Internet from any location at any time. Using weather stations and their sensors to create a mobile application that analyses and visualizes the weather is essential. The application makes use of a number of resources, such as global data and the SU dataset. Furthermore, one of the main components improving the mobile application's speed and effectiveness is the integration of cloud computing. [10].

Real-time rainfall data is used to generate early warnings, especially for areas that have been previously identified as possible landslip zones. The information is gathered from 160 carefully positioned automated rain gauges located throughout the nation's highlands. In areas at risk of landslides, the public is sent evacuation notices whenever there is 150 mm of precipitation in a 24-hour period. The final threshold for an evacuation warning has been determined to be 150 mm of rain over a 24-hour period. Local media outlets are used to distribute all early warning alerts. [11].

Making decisions regarding the management and conservation of elephant populations requires a thorough understanding of their demographics. There are few studies on the demographics of the elephant population in Sri Lanka; the 2011 census found 5,789 elephants overall. Elephants are spread across 17 out of the 25 districts in Sri Lanka. The Mahaweli region has the highest elephant population, with 1,751 elephants. Other notable concentrations include 1,573 elephants in the Eastern region, 1,189 in the North-Western region, and varying numbers in the Southern, Northern, and Central regions (1,086, 233, and 47 elephants, respectively) according to data from the Department of Wildlife Conservation in 2012. [12].

The study involved gathering primary records from sources such as the Anuradhapura Control room of Sri Lanka Railways, data from the Wildlife Department, conducting interviews with drivers who had experienced elephant accidents, and personally observing the accident sites through cab rides during both daytime and nighttime. Accidents have been occurring in both the Batticaloa and Trincomalee branches of the Eastern Railway line during this time period, which is a noticeable trend. In response to locomotive drivers identifying a lack of visibility as the primary issue, an ergonomic analysis related to visibility was conducted across various types of locomotives. In order to address the main problem of poor night vision, we came up with an innovative solution that had never been used in railroads or other similar applications. A long-range, outdoor-ready night vision camera was chosen and installed on the locomotive's short hood side. [13].

The 2011 Alawwa rail accident occurred when a passenger train collided with a stationary Intercity Express near Alawwa railway station, resulting in five fatalities, including a French national and a Thai Buddhist monk. The accident, possibly caused by human error, involved the S11 train hitting the observation car at the end of the stationary train. [14].

An elephant was fatally struck by the Menagaya night mail train en route from Batticaloa to Colombo Fort between Welikanda and Poonani railway stations around 10 p.m. This unfortunate incident occurred just three days after another elephant lost its life in a collision with the Pulatisi train at approximately 9.15 p.m., close to the current location. [15].

The Polgahawela level crossing accident occurred on April 27, 2005, at 8:30 local time, involving a collision between a bus traveling from Galkiriyagama to Colombo and a train at a level crossing in Yangalmodara, near Polgahawela in Kurunegala district. Tragically, the accident resulted in the loss of 41 lives. [16].

The before mentioned news inspires us to offer a solution to reduce the possibility of accidents as a result of our study, in order that we may be able reduce the causes of train accidents. The second goal is to decrease the impact of accidents, whether they include bulls or elephants colliding with larger vehicles.

Title	Object Detection	Objects detection on Different Lighting conditions	Rail Track Edge Detection	Weather Information & Prediction	Location Awareness	Premature Land slide Recognition	User Interface
Railway Track Specific Traffic Signal Selection Using Deep Learning	✕	✕	✓	✕	✕	✕	✕
Real-Time Detection and Recognition of Railway Traffic Signals Using Deep Learning	✕	✓	✕	✕	✕	✕	✕
Railroad Near-Miss Occurrence Detection and Risk Estimation System with Data from Camera Using Deep Learning	✓	✕	✓	✕	✕	✕	✕
A Smart Driver Alert System for Vehicle Traffic using Image Detection and Recognition Technique	✕	✕	✕	✕	✕	✕	✓
An intelligent railway surveillance framework based on recognition of object and railway track using deep learning	✓	✕	✓	✕	✕	✕	✕
Railway track tracer system for creature detection	✓	✕	✕	✕	✕	✕	✓
Intelligent Driver Monitoring System for Safe Driving	✕	✕	✕	✕	✕	✕	✓
Detection of Locomotive Signal Lights and Pedestrians on Railway Tracks Using Improved YOLOv4	✓	✓	✕	✕	✕	✕	✕
Railway Sign Detection and Classification	✕	✓	✕	✕	✕	✕	✕
Mobile Application for Visualizing Weather Data in Oman Based Cloud Computing	✕	✕	✕	✓	✕	✕	✓
Landslide Disaster Risk Reduction Strategies and Present Achievements in Sri Lanka	✕	✕	✕	✕	✓	✓	✕
Human-Elephant Conflict in Dimbulagala, Sri Lanka: Causes and Solutions	✕	✕	✕	✕	✓	✕	✕
Intelligent Vision-Based Driver Assisted System for Trains – Elephants Accidents	✓	✕	✕	✕	✕	✕	✓
Proposed System	✓	✓	✓	✓	✓	✓	✓

Table.1. Gap Analytics Table

3. Problem

Ensuring the safety of railway operations is a challenging task, especially for locomotive pilots. They frequently encounter unexpected obstacles on the tracks, including large vehicles and wild animals like elephants and buffaloes Collisions between trains and large animals can lead to significant consequences, affecting both the trains and the animals involved Unpredictable changes in weather, such as sudden shifts that lead to incidents like landslides due to heavy rainfall, also contribute to train accidents. This poses a significant risk to both passengers and animals. Addressing these challenges is crucial to prevent accidents, minimize disruptions, and improve the overall safety and efficiency of the rail journey.

4. Aim and Objective

4.1. Project Aim

The aim of this research project is to design, develop, and implement an innovative web application for locomotive pilots, leveraging advanced computer vision technologies. The application will be tailored to enhance railway safety and operational efficiency by accurately detecting and interpreting objects on the railway track. Additionally, the system will incorporate real-time location and weather awareness to provide train drivers with crucial information about their current and upcoming route conditions. Through seamless camera integration, efficient data processing, and intuitive user interface design, the project aims to revolutionize the way locomotive drivers perceive and interact with their environment, contributing to safer and more reliable railway transportation systems.

4.2. Project Objectives

Precise Object Detection on Railway Track
Implement advanced object detection algorithms capable of accurately identifying stationary and moving objects on the railway track, focusing on obstacles such as animals, vehicles, and other hazards. Ensure high accuracy and reliability under varying environmental and lighting conditions.

Real-time Location and Weather Awareness
Integrate cloud-based technologies and real-time data sources to provide locomotive pilots with up-to-date information about their geographical position and current weather conditions along the railway route. Enable the application to deliver timely updates on factors such as precipitation, visibility, and wind speed to assist drivers in making informed decisions.

Efficient Real-time Data Processing
Develop an efficient system for processing live camera feeds and other real-time data streams promptly. Minimize latency and optimize the processing pipeline to provide instantaneous feedback to locomotive pilots about detected objects, location, and weather conditions.

Intuitive User Interface Design

Create an intuitive and user-friendly web interface for locomotive pilots, displaying real-time information about detected objects, weather, location, and other relevant data in a clear and easily understandable manner. Implement voice enabled output functionality to allow drivers to interact with the application seamlessly.

5. Methodology

Our web application focuses on three main components: obstacle detection, early meteorological recognition, and potential hazard detection. First, we trained the system with frames of images taken from a specialized obstacles dataset. This dataset records images of humans, large vehicles, bulls, and elephants under various lighting and weather conditions. Subsequently, the trained model is used to detect obstacles inside individual frames. Then, frames with obstacles are classified using deep learning modules to identify, among other things, if bulls and elephants exist near railroad tracks, as well as human beings and large vehicles within the railroad tracks. The system immediately notifies the locomotive pilot via the user interface and voice output.

Regarding an early meteorological process: specify the goals and reach of the early warning system, including the use of cloud machine learning engines for model training and cloud storage for meteorological data storage. Using reliable sources or APIs, connect the most recent meteorological data to Google Cloud Services. Verify that the weather data includes the necessary information regarding humidity, temperature, wind speed, mist, fog, and precipitation. Obtain information on the amount of rainfall, visibility, and other important meteorological factors that have an impact on railway safety. To identify trends and connections between potential weather-related hazards to railway operations, develop a model. Using Google Cloud tools, validate and assess the model against a range of meteorological conditions, some of which are not present in the training set. By using voice commands, you can set up warning thresholds that will activate when bad weather is detected, based on the severity of the prevailing meteorological circumstances.

Describe the different risk categories and their effects on railway operations. Gather relevant information from many sources, such as maintenance records, historical incident reports, and details on the railway infrastructure. Surveys and interviews should be used to learn about their opinions on possible risks and how they might affect railway safety. Utilizing elements including weather data, landslide conditions, and past bull and elephant collision occurrences, train the models to recognize patterns suggestive of dangerous situations. Make sure the system is always updating its hazard estimations using the most recent data. Make use of geographic information systems (GIS) to map and examine the possible dangers' spatial distribution. Set the system up to use voice commands and a user interface to generate alerts when the detected risk rises above predetermined levels.

The below figure shows a graphical illustration of the proposed solution.

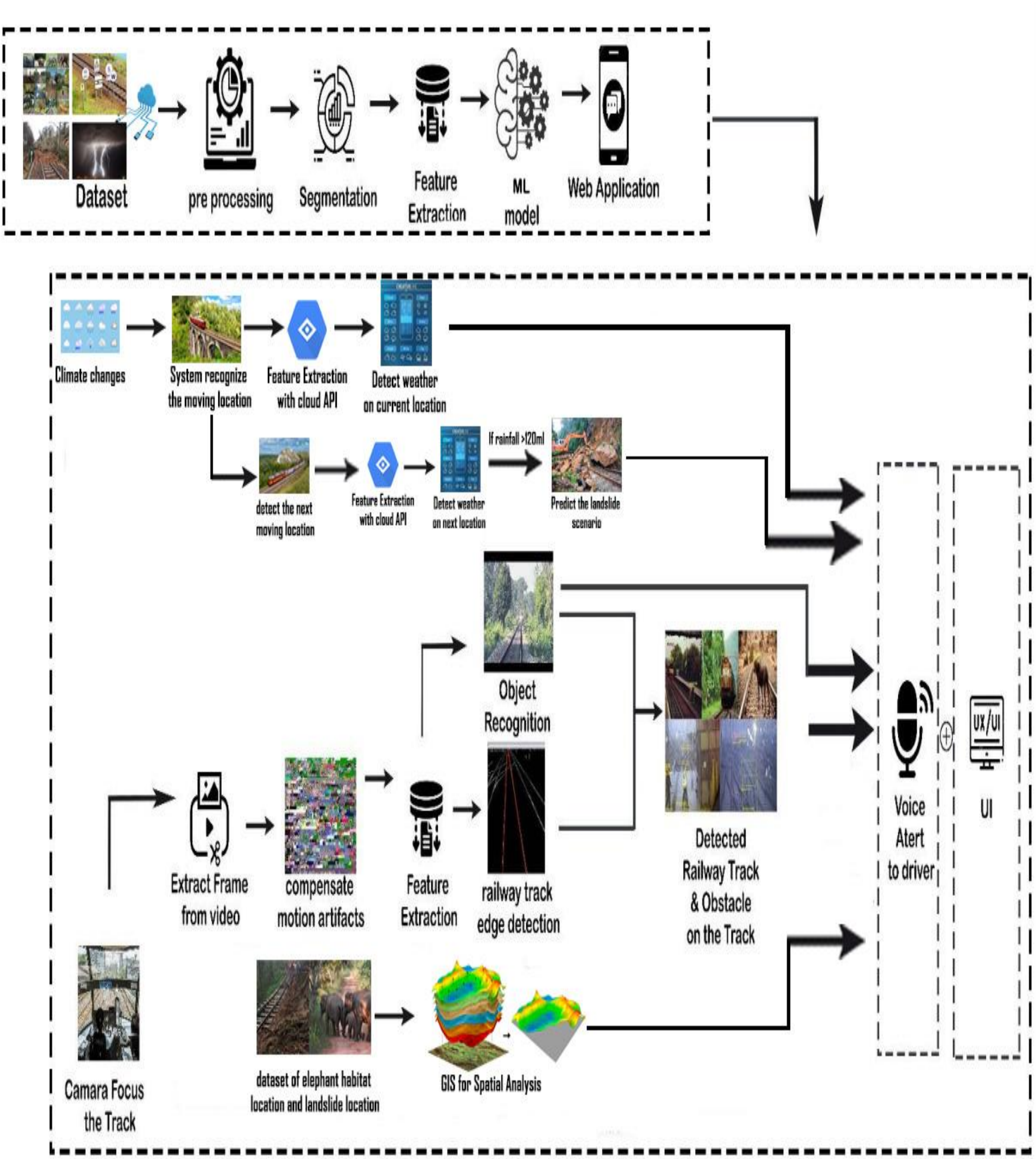

Figure.1. Graphical Illustration

Proposed Solution

Our initiative intends to improve railway safety by using computer vision and cloud-based technology. For this activity, we utilize a camera. The camera is fixed in front of the train to capture the locomotive driver's view. If the camera detects an object, such as an elephant, buffalo, human, or large vehicle, on the railway track, our system alerts the locomotive driver, providing information about both the current and upcoming location, as well as the weather conditions. The system derives that information from cloud services. Furthermore, our system provides a visual interface with voice alert for locomotive drivers about Meteorological information, and locations.

6. Project Time Plan

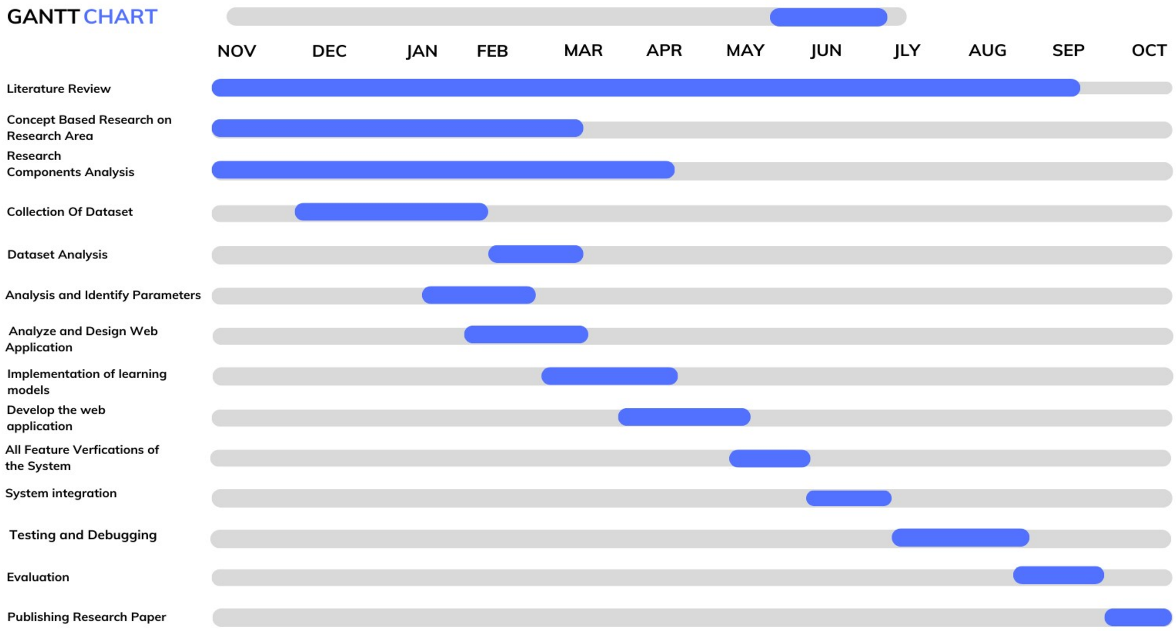

Figure.2. Gantt chart

7. Resource Requirement and Budget

Requirements	Budget
IR Cameras (Renting)	20000
Camera mounts (Renting)	2000
Laptop (Available)	0
Power source (Renting)	5000
Speaker (Renting)	2000
Internet	5000
Dataset (Started collecting, Travelling charges)	20000
Total	**54000**

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