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Predictive Analysis on Crowd Management System using Recurrent Neural Networks

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Abstract—Crowd control is a public policy technique in which massive crowds are handled in order to avoid the emergence of possible issues or threats that may occur as large crowds assemble. This project's main goal is to analyse CCTV visuals in real time in order to automatically detect crowd distribution and provide statistical data to users. The goal of the project is to decide the RNN prediction value and quantify the crowd count for future prediction. In this Pandemic, social distancing is critical; otherwise, there is a high chance of individuals being infected with the virus. As a result, we will compute the crowd density of a certain area using security cameras that are present at several locations. If the crowd density in a given area is found to be higher than the permitted crowd density, we will notify the police authority, who may be able to track down others that are not abiding by the government's laws, i.e., we will avoid big crowd events that could cause more people to be impacted. The projected values achieved in this project will be used by people to avoid periods where there is overcrowding. It also keeps track of crowds and waiting times at key locations such as bus stops, train stations, airports, religious sites, and campus canteens. People will use the expected RNN value to review the actual crowd level dynamics in markets and determine whether or not to go there. People may use this model to compare crowd sizes and skip the worst times of the day.

Index Terms:RNN; crowd counting; COVID19

I. INTRODUCTION

The human population has been steadily rising in recent years. Huge crowds of chaos arise from a crowded crisis, resulting in pushing, mass-panic, stampedes, or crowd crushes, and a loss of control. The rapid spread of the virus that causes COVID-19 has caused widespread concern around the world. In this Pandemic, social distancing is critical; otherwise, there is a high risk of people being infected with the virus. Large crowding in public places will hasten the spread of the virus. People are reluctant to leave their homes in this situation. Since the virus can spread from person to person, crowding is a significant factor that is linked to disease incidence and severity. To stop the virus from spreading, we must first control the crowd.

Recurrent Neural Networks are proposed as a solution to estimate the size of an incoming crowd RNNs (recurrent neural networks) are a type of neural network that can be used to model sequence data. Other algorithms are unable to generate predictive results in sequential data. RNNs can hold their state from one iteration to the next by feeding the

next phase their own output. In a recurrent neural network, you not only fe ed the network data, but you also feed it the network's previous state. Since very large architectures can be successfully trained, the Long Short-Term Memory network, or LSTM network, is a form of recurrent neural network used in deep learning. The goal is to provide an effective RNN value to measure the crowd count for future prediction. People should use the expected values to prevent overcrowding at times when it is most likely to occur. During COVID-19, the bigger the audience, the more likely everyone in it will be infected with the virus; this project aims to reduce large crowd gatherings, which may result in more people becoming infected.

II. LITERATURE SURVEY

A feedforward neural network with an internal memory is known as a recurrent neural network. RNN is repetitive in nature since it performs the same operation for each data input, and the current input's output is dependent on the previous computation. The output is copied and sent back into the recurrent network after it is generated. It considers the current input as well as the output it has acquired from the previous input when making a decision.[1]PCRN consistently outperforms state-of-the-art methods for crowd density prediction across two taxi datasets from Beijing and Singapore, thanks to an optimization-based model that uses pyramidal convolutional recurrent network architecture.[2] designed, trained, and benchmarked a data-driven procedure to forecast crowd movements that can predict crowd movement in real time using GPS traces and training a Recursive Neural Network (RNN) with a Gated Recurrent Unit (GRU) and six benchmark models to forecast the next location of pedestrians, and they came to the conclusion that using cell sequence data and an RNN-GRU crowd movements at large scales can be predicted. [3] ST-ResNet is a deep-learning-based method for collectively forecasting crowd inflow and outflow in each and every area of a community. This model is tested on two different types of crowd flows in Beijing and New York, and it performs well. [4]presents a solution for ensuring successful management and protection in large-scale public events in terms of WiFi-based crowd counting and LSTM neural network-based forecasting, concluding that Convolutional LSTM provided the best output among different LSTM models. [5] is a deep convolution neural network (DCNN)-based system for crowd counting in near real time. The machine makes use of an NVIDIA GPU processor to take advantage of the parallel computing architecture and process video feeds from a camera quickly and efficiently. The model is thoroughly trained by presenting it with a variety of situations, such as overlapping heads, partial visibility of heads, and so on. In a dense population, this method provides considerable precision in calculating the head count in a fair period of time. In cases where manual counting is impractical, the proposed method performs admirably. Deep learning also helps the machine to operate in a number of settings and to learn from new inputs on a continuous basis. [6] gives an overview and performance comparison of crowd counting strategies focused on density map estimation using convolutional neural networks (CNN). It's a thorough review and comparison of crowd counting methods based on the UCF-QNRF dataset, which contains the most crowd count images and head annotations in the public domain. The network structures of the different models, the method of learning targets, and the loss function were all summarised in this article, which looked at the network models for crowd counting that have been published in recent years. The architecture of the BL model was replaced to check the robustness of the BL model data processing system and loss function, as the BL model performed well in the evaluated networks. [7] To predict the density map for a given crowd image, a combination of deep and shallow completely convolutional networks is used. This combination is used to capture both high-level semantic information (face/body detectors) and low-level features (blob detectors) that are needed for crowd counting at large scale variations. On the complicated UCF CC 50 dataset, this approach outperforms state-of-the-art approaches. [8] The proposed MCNN accepts images of any size or resolution as input. The features learned by each column CNN are sensitive to differences in people/head size due to perspective effect or image resolution by using filters with receptive fields of different sizes. On all of the datasets used for testing, this model outperforms state-of-the-art crowd counting methods. Furthermore, by fine-tuning only the last few layers of the trained model, this model trained on a source domain can be easily transferred to a target domain, demonstrating the proposed model's generalizability.[9] is a crowd counting deep convolutional neural network (CNN) that is trained with two associated learning objectives: crowd density and crowd count. For both goals, the proposed switchable learning strategy is able to achieve a better local optimum. Other hand-craft features, such as the learned deep model, are better at portraying crowd scenes than the learned deep model. [10] proposed a global-residual two-stream recurrent network that leverages consecutive crowd video frames as inputs and their corresponding density maps as auxiliary information to predict future crowd distribution and demonstrated that the architecture is capable of predicting crowd distribution in various crowd scenarios and can be applied to a variety of crowd analysis applications.Switching convolutional neural networks (S-CNN) was used in [11] to boost crowd detection and counting accuracy. Inter scene variation was not taken into account in previous methods, but with S-CNN, inter scene variation and semantic analysis are taken into account to increase count estimation. The switching convolutional neural network has the benefit of using intra-image crowd density variance to increase the accuracy of people localization. The proposed algorithm was tested on the Shanghai Tech Part A dataset, and the Mean Average Error value was found to be 98.87. [12] proposes a model for crowd counting in public areas with high and low densities. The model operates in a variety of scenarios and requires no prior knowledge. A Deep CNN model (DCNN) is developed using a convolutional neural network (CNN) structure with two fronts and a small kernel scale. This paper introduces a model for accurately counting people from a single picture with any random crowd density and camera perspective. As compared to state-of-the-art models, the findings show that our proposed model achieves a lower MAE. An end-to-end predictive model is designed to take in tweets as additional inputs to forecast the potential movement of crowds in an urban environment [13], which is implemented using a deep neural network-based method. As additional signals to the predictive model, it extracts different features from tweets, such as tweet counts, tweet tenses, and sentiments. By expanding an existing state-of-the-art crowd flow prediction model known as ST-ResNet and incorporating various linguistic features from real-time tweets, this paper investigated the efficacy of using tweets to crowd flow prediction. It was discovered through empirical experiments with two separate datasets used to reflect traffic flows in Singapore that tweets can increase prediction accuracy by up to 3.28 percent on average, and that this improvement is statistically important. A research on Crowd Identification and Density Analysis for Safety Management can be found in [14]. It states that using face and identification, pattern recognition technique aids in estimating crowd detection count and density. Because of the Deep Convolutional Neural Network, the counting efficiency has gradually improved. The deep learning model is very effective for crowd counting and analysis, and we discussed some methods of Convolutional Neural Networks, which is our basic system for learning efficient features for counting, in this report. It is an end-to-end training method that performs inference based on the entire picture. Large labelled datasets are needed for better crowd counting results. [15] suggests a convolutional LSTM (ConvLSTM) version of a deep learning model for crowd counting. This approach thoroughly captures both spatial and temporal dependencies, unlike previous CNN-based approaches. In addition, this paper introduces a bidirectional ConvLSTM model that can access long-range information in both directions. On the UCF CC 50 dataset, the Mall dataset, and the WorldExpo dataset, this model outperforms existing crowd counting approaches, and on the UCSD dataset, it achieves comparable performance. [16] defines a device that consists of two key components: a server-side application connected to IP cameras to monitor crowd levels in specific locations, and a smartphone application with varying user rights to receive alarms from the server-side application. This structure offers a quick and easy way to communicate and warn all device users, reducing the risk of a large crowd. This framework issues an early warning only seconds after the amount reaches the specified limits, allowing for a better chance of solving the problem with minimal losses or damages and avoiding the danger of a large crowd. The device was also put through its paces with interface, unit, and usability tests to ensure that it was likely to work. It elicited an efficient response from the users. The results of the tests were positive. The latest convolutional-neural-network-based crowd-counting techniques are checked, categorized, evaluated, and a thorough performance assessment is given. The paper also discusses the possible applications of crowd-counting techniques focused on convolutional neural networks. A thorough analysis of CNN-CC and density-estimation techniques was discussed in this paper. It divided CNN-CC techniques into three categories: network-, image-view, and training-CNN-CC. [18]proposed a novel two-level data augmentation-based system for counting people in still photos. This method merged high- and low-level feature extraction into a single system. This model converts the training samples to polar coordinates first, then uses the magnitude and skeleton of the resulting image to feed the original training samples directly to the deep convolutional neural network. The technique achieves less calculations and better execution than a few later related works, according to test results. Since the head is the most prominent part of the body in a crowded scene, [19] senses it. The head detector is built on a cascade of boosted integral features that is state-of-the-art. This paper proposes a method for counting crowds in photos based on head detection and gradient orientation interest points. [20]proposed a novel multi-branch scale aware attention network that takes advantage of convolutional neural networks' hierarchical structure to produce multi-scale density predictions from different layers of the architecture in a single forward pass. This paper proposed a straightforward but efficient method for estimating the size of each head in a picture. On all measurement measures, this approach generated state-of-the-art results on four demanding crowd counting datasets. [21] employs a method that adaptively encodes the scale of contextual data needed to reliably predict crowd density. As an input to a deep net, this method provides an explicit model of perspective

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distortion effects, which significantly improves crowd counting efficiency. It produces much better density estimates in high-density areas, in particular. Paper [22] reviewed over 220 articles in order to perform a thorough and systematic analysis of crowd counting models, concentrating on CNN-based density map estimation methods. The studies offered plausible explanations for the problem of object counting in other areas, as well as logical inferences and forecasts for the potential development of crowd counting. [23] proposes a deep spatial regression model (DSRM) based on Convolutional Neural Networks (CNN) and long short term memory for counting the number of individuals present in a still image with arbitrary perspective and arbitrary resolution (LSTM). The adjacent local counts are strongly associated with the overlapping patches divided technique, and it was tested on many challenging crowd counting datasets, with the results demonstrating that the deep spatial regression model outperforms state-of-the-art approaches in terms of reliability and effectiveness.

III DATASET

The dataset gathered consists of columns namely date, local holiday, time, weather and count.

A	B	C	D	E
Date	Local holiday	Time	Weather	Count
737616	1	0	38	20
737616	1	3	31	5
737616	1	5	37	15
737616	1	6	30	25
737616	1	8	33	70
737616	1	10	35	55
737616	1	11	38	70
737616	1	13	37	80
737616	1	14	38	45
737616	1	16	31	61
737616	1	17	28	75
737616	1	18	31	83
737616	1	19	34	85
737616	1	19	37	81
737616	1	20	30	79
737616	1	21	29	50
737616	1	22	32	43
737616	1	22	26	38
737616	1	23	35	25
737616	1	23	32	23
737617	1	0	25	20
737617	1	1	36	13

The column count represents the head count which depends upon the other four parameters. This dataset was used to train the model to predict the future crowd count. This dataset consists of approximately 5000 datas.

IV METHODOLODY

In this section, we first define the problem and then introduce the proposed model and its components:(1) Recurrent Neural Network (2) Linear Regression. Finally the performance of the two models are compared .

Linear Regression

By fitting a linear equation to observed data, linear regression attempts to model the relationship between two variables. One variable is treated as an explanatory variable, while the other is regarded as a dependent variable.

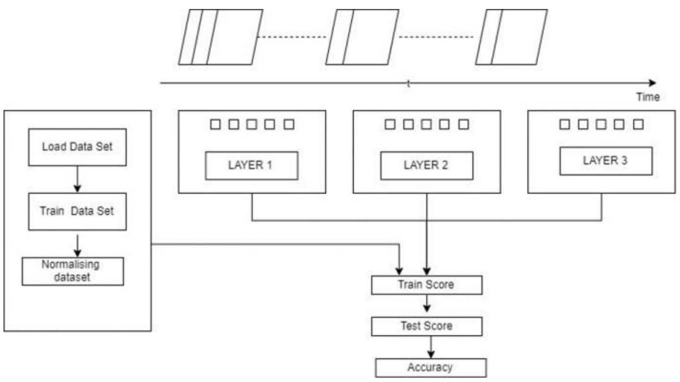
A modeler should first decide whether or not there is a relationship between the variables of interest before attempting to fit a linear model to observed data. This does not necessarily mean that one variable affects the other, but rather that the two variables have a substantial relationship. When evaluating the intensity of a relationship between two variables, a scatterplot may be useful. If the proposed explanatory and dependent variables do not appear to be related, fitting a linear regression model to the data is unlikely to yield a useful model. The correlation coefficient, which is a value between -1 and 1 indicating the frequency of the association of the observed data for the two variables, is a useful numerical measure of association between two variables.

Recurrent Neural Network

Neural Networks are a series of algorithms that are programmed to identify patterns and closely imitate the human brain.A feedforward neural network with an internal memory is known as a recurrent neural network. RNN is repetitive in nature since it performs the same operation for each data input, and the current input's output is dependent on the previous computation. The output is copied and sent back into the recurrent network after it is generated. It considers the current input as well as the output it has acquired from the previous input when making a decision. RNNs, unlike feedforward neural networks, can process sequences of inputs using their internal state (memory). As a result, tasks like unsegmented, linked handwriting recognition or speech recognition are possible. All of the inputs in other neural networks are independent of one another. In an RNN, however, all of the inputs are connected to one another.

Long Short-Term Memory (LSTM) networks are a modified variant of recurrent neural networks that make it easier to recall information from the past. Here, the RNN's vanishing gradient problem is solved. Given time lags of uncertain length, LSTM is well-suited to identify, process, and forecast time series.

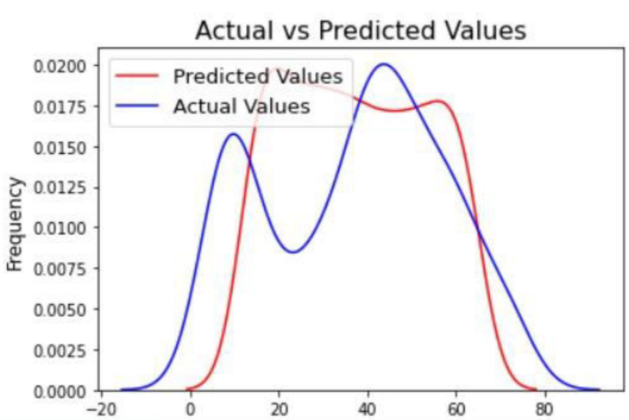
Back-propagation is used to train the model.



V RESULT

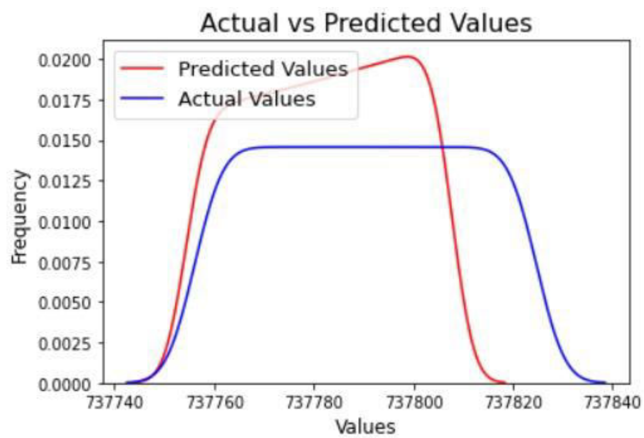
LINEAR REGRESSION:

The accuracy got using Linear Regression is 64.075 and RMSE value is 12.24 . Linear Regression gave a very less accuracy and high RMSE value for the manually generated dataset as it could take only two parameters as input . In order to improve the accuracy and reduce the RMSE value Recurrent Neural Network model was used as it performs the same function for every input of data while the output of the current input depends on the past one computation. Also Recurrent Neural Network can take multiple parameters as input resulting in better accuracy.



RECURRENT NEURAL NETWORK:

The absolute mean error value is 0.6845 for the manually generated dataset. The outputs, show that the Recurrent Neural Network gave better results than Linear Regression. This is mainly because Recurrent Neural Network keeps track of the past computations, making it a better performing model and thus resulting in better accuracy.



VI FUTURE SCOPE

Masses of bodies, particularly humans, are the subjects of these crowd tracking analyses that include how a particular crowd moves and when a movement pattern changes.Researchers use the data to predict future crowd movement, crowd density, and plan responses to potential events such as those that require evacuation routes.Applications of crowd analysis can range from video game crowd simulation to security and surveillance.This application on slight modification can be used as adaptive traffic signal control system. By analysing the traffic in the roads the time duration of the signals can be modified respective to the traffic in real time.The application also holds the potential to be implemented at indoor spaces like college campus and malls where crowd density can be analysed.The application can also be modified to help the farmers in harvesting. Farmers can predict the harvest season based on previous year data which will help them to harvest properly.

VII CONCLUSION

In this paper, linear regression model and recurrent neural network model were compared to see which model performed better to predict the future crowd density. The models were evaluated using a manually gathered crowd count dataset. The dataset was run using the two models and it was found that the RNN model produced significantly better results compared to the linear regression model.

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