AN ENSEMBLE LEARNING FRAMEWORK FOR VISIBILITY PREDICTION IN INDO-GANGETIC REGION

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1 INTRODUCTION

Visibility conditions depend mainly on different phenomena such as changes in air-mass, winds, temperature profiles etc. These phenomena in turn depend on the type of synoptic system affecting a region. Poor visibility condition has an ill effect on the air traffic and transportation system Fabbian et al. (2007), which can badly impact the economy Holtz-Eakin & Wachs (2011). Moreover, poor visibility due to hazy weather decreases road safety and increases the risk of traffic congestion Gao et al. (2020). There are a lot of research works regarding the estimation of visibility applying machine learning algorithms (mostly regression techniques) using the meteorological data of various regions Gultepe et al. (2006); Li et al. (2017). Li et al. Li et al. (2017) developed an advanced numerical prediction model for detecting the factory emission which were further used to build a visibility prediction system. Ortega et al. Ortega et al. (2019) compared five different machine learning classifiers to determine the visibility in the region of Florida in USA. Castillo et al. Castillo-Botón et al. (2022) explored the performance of different classification and regression techniques to predict low visibility events over a data from Mondonedo weather station at Galicia in Spain. There are many other research works for visibility prediction using machine learning algorithms and artificial neural network (ANN) techniques Bari & Ouagabi (2020); Im Cho & Palvanov (2019). However, to our knowledge, none of these works focus on analysing the performance of machine learning techniques for visibility estimation of the Indo-Gangetic plane in India. Indo-Gangetic plane witnesses widespread fog (a term used for conditions when visibility is less than 1 km), primarily during winter. The increase in fog and poor visibility has become prominent over the last 50 years in this region. Despite the large spatial extents, the localised physical nature and spatio-temporal variations of visibility at various scales pose huge challenges in its accurate estimation. Therefore, it is crucial to analyze the factors and their impact on visibility using better data-driven approaches.

2 PROPOSED FRAMEWORK

In this spirit, a regression framework has been developed to estimate the visibility in the Indo-Gangetic plane in two stages. Note that the meteorological data generally contain mixture of numerical and categorical features and for many features certain values may not be recorded due to system failure . In the first stage, some standard feature engineering schemes has been used to identify potential spatio-temporal features of the meteorological data. The surface meteorological data that is used in this work contain the data from different weather stations in the Indo-Gangetic region, collected from hourly observations contained in US National Oceanic and Atmospheric Administration (NOAA) surface data repository Rutledge et al. (2006). We have grouped the data of each weather station with a unique id to combine them to diminish the effect of the missing values as individual features of a particular weather station have less variations than the other stations. Note that the data set has lot of missing values of individual features and hence different standard schemes have been used here to deal with these missing values. The median of all the values of a particular feature is used here to replace the missing values for that feature as the median is a representative of the given feature Lin & Tsai (2020). Similarly for categorical features, mode of a feature instead of median is used to replace the missing values for that feature. Subsequently, to apply the regression techniques on this data set, categorical features are transformed to numerical values following one hot encoding scheme Seger (2018), which is an widely used scheme in this regard. Subsequently, XGboost method Luckner et al. (2017), a state of the art regression model is used to derive relation between different features to estimate the target variable, i.e., visibility. The XGboost method is used in the proposed framework to estimate the visibility from the given meteorological data as it

Table 1: Experimental Results of Different Methods for Visibility Estimation

Evaluation Measure	AB	DT	ENet	LGBM	LR	LO	RF	RG	RNN	Proposed
MAE	2.35	1.37	3.10	0.30	3.19	3.12	1.03	2.7	2.21	**0.03**
RMSE	7.77	6.07	8.79	0.45	8.80	8.80	4.99	8.10	1.91	**0.06**

performed very well in different recent applications Pan (2018); Li et al. (2019). XGboost is an efficient and scalable implementation of gradient boosting technique that uses the sparsity-aware split-finding approach to train the method efficiently on sparse data Chen & Guestrin (2016).

3 Experimental Analysis

The dataset is collected from 31 different cities in the Indo-Gangetic plane and has several spatio-temporal meteorological parameters. The dataset is collected from hourly observations contained in NOAA surface data repository Rutledge et al. (2006). The original dataset has 934807 instances from different weather stations and 121 features for each instance. Out of these 121 features, 104 features have been removed as they have more than 50% missing values, but for rest of the features, the missing values were replaced by the median or mode of the other values of the features as stated in section 2. The experimental results reported in Table 1 are obtained using these 17 features of the test data. The performance of the proposed framework using XGBoost algorithm is compared with the state of the arts viz., linear regression (LR) Chan et al. (1999); Montgomery et al. (2021), decision tree (DT) regression Wantuch (2001); Loh (2011), random forest (RF) regression Kim et al. (2021); Loh (2011), lasso (LO) regression Castillo-Botón et al. (2022); James et al. (2013), ridge (RG) regression Uyanık et al. (2021); Marquardt & Snee (1975), LightGBM (LGBM) regression Yu et al. (2021); Ke et al. (2017), adaptive boosting (AB) regression Jakhar et al. (2021); Solomatine & Shrestha (2004), elastic NET (ENET) regression Castillo-Botón et al. (2022); Zou & Hastie (2005) and RNN based regression Jonnalagadda & Hashemi (2020); Medsker & Jain (2001) techniques in terms of RMSE Chai & Draxler (2014); Qi et al. (2020) and MAE Chai & Draxler (2014); Qi et al. (2020). It may be noted that the proposed method is iterated for 1000 times to avoid the effect of randomization. The data used for experiments here is randomly split into 90% as training data and 10% as test data. The training data is used to tune the parameters of individual regression techniques following 10-fold cross validation technique. Subsequently, the best set of parameters is implemented on the test data for each method. Note that a low score of MAE and RMSE is desirable to indicate the better performance of a regression technique than another method. Table 1 shows that the performance of the proposed method is better than the other techniques in terms of MAE and RMSE. It may be noted that both MAE and RMSE of the proposed one is almost 0, which indicate the method is working reasonably well. These results clearly show the effectiveness of the proposed framework to estimate the visibility of an area. We have performed the paired t-test Ruxton (2006) on the results of the proposed framework and the other methods in Table 1 to test the statistical significance. The p-value threshold is set to 0.005 here i.e., anything below 0.005 rejects the null hypothesis. It has been found that 16 cases out of 18 cases are statistically significant when the proposed method beats other techniques in Table 1. The results are inconclusive in the rest two cases in Table 1. Thus it can be concluded that the proposed one performs significantly better than the other techniques in 88.88% (16/18) cases in Table 1.

4 Conclusions

A regression framework is developed here to automatically estimate the visibility of different areas for the upcoming days using the data of the Indo-Gangetic region, which outperforms the state of the arts. Although the error rate of the proposed method is very low, but still there are scopes to improve the performance further by using the meteorological data of various other regions across globe. Note that the framework is evaluated based on the ground truths (i.e., the visibility recorded in the past) of the meteorological data of Indo-Gangetic region. Furthermore, no domain expert is involved in this work and no specific domain knowledge is used to build the framework. Therefore we believe that the method has the potential to be used for visibility estimation of any area across globe using the meteorological data. In future, we plan to explore the performance of this framework on the meteorological data of other regions where visibility estimation is crucial.

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