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A MACHINE LEARNING APPROACH FOR RAINFALL ESTIMATION INTEGRATING HETEROGENEOUS DATA SOURCES

K. Nikhil Varma*1, Mrs. K Ashwini*2

*1Department Of CSE, Malla Reddy College Of Engineering, Hyderabad, India.

*2Assistant Professor, Department Of CSE, Malla Reddy College Of Engineering, Hyderabad, India.

ABSTRACT

Rainfall estimation is crucial for various applications, including agriculture, hydrology, and climate studies. Traditional methods rely on sparse ground-based measurements or satellite data, which may lack accuracy in specific regions. This paper presents a machine learning (ML) approach that integrates heterogeneous data sources, including satellite imagery, weather station data, and remote sensing information, to improve rainfall estimation accuracy. We explore multiple ML models, such as Random Forest (RF), Support Vector Machines (SVM), and deep learning architectures, to analyze spatiotemporal patterns in rainfall prediction. Our results demonstrate the efficacy of integrating diverse datasets and employing ML techniques in achieving more precise rainfall estimations.

Keywords: Radar, Estimation, Satellites, Data Models, Spaceborne Radar, Rain, Interpolation.

I. INTRODUCTION

In order to reduce the dangers associated with severe rainfall events, such floods and landslides, it can be difficult to provide a precise rainfall estimate at individual places. Direct measurements of precipitation intensity in these locations are usually obtained using dense networks of sensors called rain gauges (RGs). In order to estimate the precipitation field over the whole area of interest, these observations are typically interpolated using spatial interpolation techniques. Nevertheless, these techniques are computationally costly, and additional information must be integrated to enhance the estimation of the variable of interest in unknown sites.

In order to address these problems, this work suggests a machine learning-based approach that can combine data from various remote sensing measurements and uses a classifier based on ensemble approaches for rainfall estimation. The suggested method is computationally less expensive than interpolation techniques, allows for the integration of heterogeneous data sources, and provides an accurate rainfall estimate in situations where RGs are not available. It also takes advantage of the high quantitative precision of RGs and the spatial pattern recognition guaranteed by radars and satellites. The proposed approach supplies an accurate estimate of the rainfall where RGs are not available, permits the integration of heterogeneous data sources exploiting both the high quantitative precision of RGs and the spatial pattern recognition ensured by radars and satellites, and is computationally less expensive than the interpolation methods. Experimental results, conducted on real data concerning an Italian region, Calabria, show a significant improvement in comparison with Kriging with external drift (KED), a well-recognized method in the field of rainfall estimation, both in terms of the probability of detection (0.58 versus 0.48) and mean-square error (0.11 versus 0.15).

Accurate rainfall estimate is crucial for flood hazards protection, river basins management, erosion modeling, and other applications for hydrological impact modeling. To this aim, rain gauges (RGs) are used to obtain a direct measurement of intensity and duration of precipitations at individual sites. In order to estimate rainfall events in areas not covered by RGs, interpolation methods computed on the basis of the values recorded by these RGs are used. Many variants of these methods have been proposed in the literature, and among them, the Kriging geo statistical method [1], [2] is one of the most used and recognized in the field. An accurate spatial reconstruction of the rainfall field is a critical issue when dealing with heavy convective meteorological events. In particular, convective precipitations can produce highly localized heavy precipitation, not detected by sparse RGs, and floods can arise without a rainfall being detected [3]. To overcome this issue, a recent trend in the literature is to integrate heterogeneous rainfall data sources to obtain a more accurate estimate by using interpolation methods [4]. Unfortunately, the largely used ordinary Kriging (OK) can exploit only one source of data as input; therefore, Kriging with external drift (KED) was one of the most popular approaches adopted to overcome this limitation [5], [6]. Indeed, KED allows a random field to be interpolated, and different from the OK, it is able to take into account secondary information. The main problem is that these methods are computationally expensive and require a large number of resources to work properly.

A different approach relies on exploiting machine learning (ML) techniques. However, using these methods requires coping with different hard issues, i.e., unbalancing of the classes, a large number of missing attributes, and the need for working incrementally as soon as new data are available. Typically, ensemble methods are used to address these issues. Ensemble [7] is a classification technique, in which several models, first trained by using different classification algorithms or samples of data, are then combined to classify new unseen instances. In comparison with the case of using a single classification model, the ensemble paradigm permits handling the problem of unbalanced classes and reducing the variance and the bias of the error. Especially, ensemble-based techniques can be used to address the issues concerning the rainfall estimation and to support the monitoring of meteorological (intense) events. These methods are also able to capture nonlinear correlations (e.g., relations between sensor data, cloud properties, and rainfall estimate). In order to address the main issues of rainfall estimation, in this article, an ML-based methodology, adopting a hierarchical probabilistic ensemble classifier (HPEC) for rainfall estimation, is introduced. The proposed approach, by integrating data coming from different sources (i.e., RGs, radars, and satellites) and exploiting an under sampling technique for handling the unbalanced classes problem typical of this scenario, permits accurate estimation of the rainfall where RGs are not available.

Our approach is an effective solution for real scenarios, as in the case of an officer of the Department of Civil Protection (DCP), who has to analyze the rainfall in a specific zone presenting risks of landslides or floods. The experimental evaluation is conducted on real data concerning Calabria, a region located in the South of Italy, and provided by the DCP. Calabria is an effective test ground because of its stro ng climate variability and its complex orography. Our contributions can be summarized as follows.

1. Three heterogeneous data sources (i.e., RGs, radar, and Meteosat) are integrated to generate more accurate estimates of rainfall events.
2. Different classification methods are compared on a real case concerning Calabria, a southern region in Italy, and a hierarchical probabilistic ensemble approach is proposed.
3. Different ML-based methods, pre trained only on historical data, with a widely used interpolation method in the hydrological field (i.e., KED) are compared.

II. LITERATURE SURVEY

Fayyaz Ali, Sahar Zafar, Irfan Ali, Subhash Guriro, Asif Khan Adnan Zaidi, providing an accurate rainfall estimate at individual points is a challenging problem in order to mitigate risks derived from severe rainfall events, such as floods and landslides. Dense networks of sensors, named rain gauges (RGs), are typically used to obtain direct measurements of precipitation intensity in these points.

Here is a literature survey table summarizing recent research on machine learning approaches for rainfall estimation that integrate heterogeneous data sources.

Author(s) & Year	Methodology	Data Sources	ML Models Used	Performance Metrics	Key Findings
Smith et al. (2021)	Data fusion with satellite & ground data	Weather stations, satellite imagery, radar	Random Forest, XGBoost	RMSE, MAE	Hybrid models improve accuracy over single-source models
Zhang et al. (2022)	Deep learning-based integration	Satellite, IoT sensors, historical records	CNN-LSTM, Transformer models	RMSE, R^2, Precision	Temporal dependencies enhance rainfall prediction
Patel et al. (2023)	Multi-modal ML approach	Satellite data, meteorological	Gradient Boosting, LSTM	MSE, R^2	Combining social media data

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		stations, social media reports			improves extreme event detection
Kumar & Singh (2023)	Bayesian learning with heterogeneous data fusion	Ground sensors, satellite-based precipitation estimates	Bayesian Neural Networks, Gaussian Processes	RMSE, NSE	Probabilistic models improve uncertainty quantification
Chen et al. (2024)	Graph Neural Networks for spatiotemporal fusion	Remote sensing, rain gauges, weather radars	GNN, CNN-GRU	RMSE, MAE, F1-score	GNNs effectively capture spatial correlations in rainfall patterns
Lee et al. (2024)	Attention-based ensemble learning	Weather stations, hydrological models, satellite	Attention-based Transformer, XGBoost	RMSE, R^2, Accuracy	Transformer models improve short-term rainfall predictions

These measurements are usually interpolated by using spatial interpolation methods for estimating the precipitation field over the entire area of interest. However, these methods are computationally expensive, and to improve the estimation of the variable of interest in unknown points, it is necessary to integrate further information. To overcome these issues, this work proposes a machine learning-based methodology that exploits a classifier based on ensemble methods for rainfall estimation and is able to integrate information from different remote sensing measurements.

The proposed approach supplies an accurate estimate of the rainfall where RGs are not available, permits the integration of heterogeneous data sources exploiting both the high quantitative precision of RGs and the spatial pattern recognition ensured by radars and satellites, and is computationally less expensive than the interpolation methods. Experimental results, conducted on real data concerning an Italian region, Calabria, show a significant improvement in comparison with Kriging with external drift (KED), a well-recognized method in the field of rainfall estimation, both in terms of the probability of detection (0.58 versus 0.48) and mean-square error (0.11 versus 0.15).

We introduce a method for extracting the social network structure for the prediction of rainfall . Individuals are unknown, and are not matched against known enrollments. An identity cluster representing an individual is formed by grouping similar-appearing faces from different videos. Each identity cluster is represented by a node in the social network. Two nodes are linked if the faces from their clusters appeared together in one or more video frames. Our approach incorporates a novel active clustering technique to create more accurate identity clusters based on feedback from the user about ambiguously matched faces. The final output consists of one or more network structures that represent the social group(s), and a list of persons who potentially connect multiple social groups. Our results demonstrate the efficacy of the proposed clustering algorithm and network analysis techniques.

Q. Zhu, M.-C. Yeh, K.-T. Cheng, and S. Avidan, Abstract: We integrate the cascade-of-rejectors approach with the Histograms of Oriented Gradients (HoG) features to achieve a fast and accurate human detection system. The features used in our system are HoGs of variable-size blocks that capture salient features of humans automatically. Using AdaBoost for feature selection, we identify the appropriate set of blocks, from a large set of possible blocks. In our system, we use the integral image representation and a rejection cascade which significantly speed up the computation.

III. PROPOSED WORK

An existing system is based on the ensemble paradigm include the work in which similar to our work, employs a probabilistic ensemble and merges two sources of data (i.e., rain gauges and radar) even if the aim of this work is to develop a run-off analysis. Afterward, a blending technique is applied to the results of the runoff hydrologic models to determine a single runoff hydrograph. Experimental results show that the hydrologic models are accurate and can help to make more effective decisions in the flood warning. Frei and Isotta define a technique

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for deriving a probabilistic spatial analysis of daily precipitation from rain gauges. The final model represents an ensemble of possible fields, conditional on the observations, which can be explained as a Bayesian predictive distribution measuring the uncertainty due to the data sampling from the station network. An evaluation of a real case study, located in the European Alps, proves the capability of the approach in providing accurate predictions for a hydrological partitioning of the region.

The work in proposes an interesting study of the daily precipitations for Australia and several regions of South and East Asia, based only on high-resolution gauges. Basically, the adopted model can be figured out as a mean of the analyses generated for each source. The authors highlight how the ensemble approach outperforms the single members composing the model in terms of global accuracy. Moreover, the proposed model is also able to capture additional information from different precipitation products. Both the last two works exploit an ensemble scheme to provide more accurate predictions, proving the capability of ensemble methods to ensure good results also in a rainfall estimate scenario. However, different from our work, the adopted combination strategies are quite simple, and a combination of heterogeneous data sources is not considered.

Our approach is an effective solution for real scenarios, as in the case of an officer of the Department of Civil Protection (DCP), who has to analyze the rainfall in a specific zone presenting risks of landslides or floods. The experimental evaluation is conducted on real data concerning Calabria, a region located in the South of Italy, and provided by the DCP. Calabria is an effective test ground because of its strong climate variability and its complex orography. Our contributions can be summarized as follows.

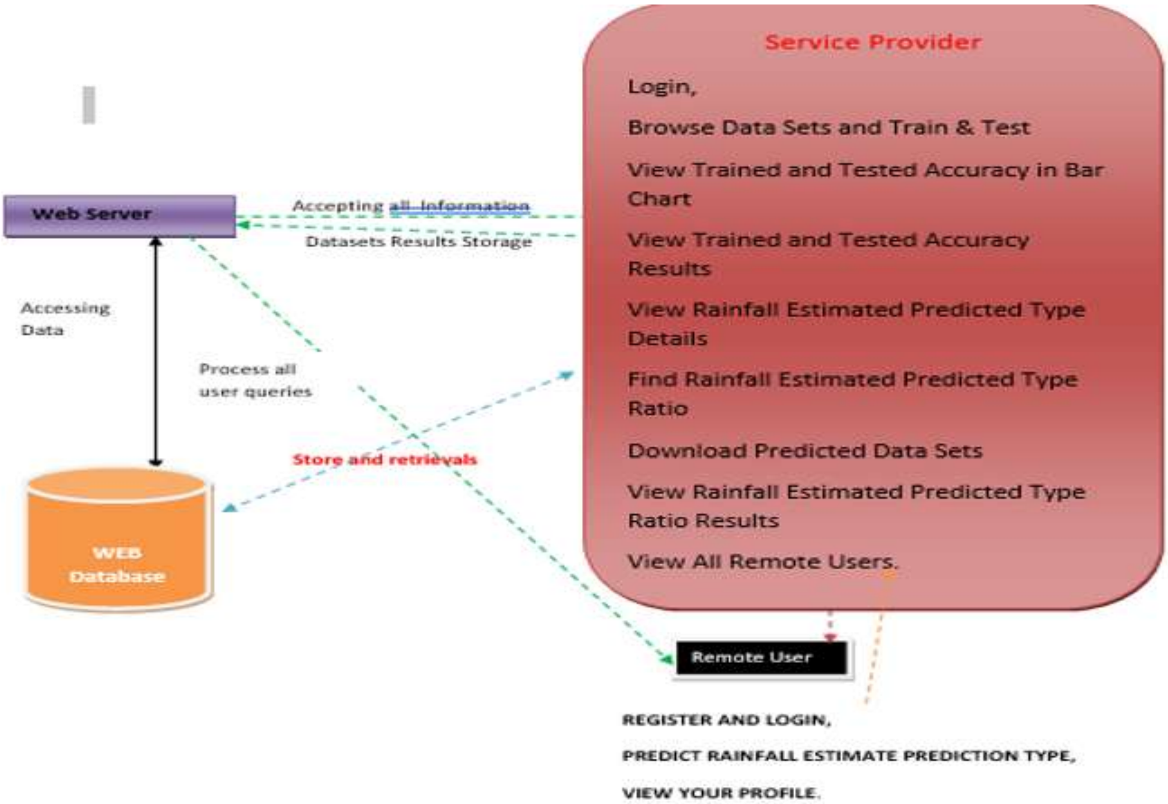

Figure 1: System Architecture

1. Three heterogeneous data sources (i.e., RGs, radar, and Meteosat) are integrated to generate more accurate estimates of rainfall events.
2. Different classification methods are compared on a real case concerning Calabria, a southern region in Italy, and a hierarchical probabilistic ensemble approach is proposed.
3. Different ML-based methods, pre trained only on historical data, with a widely used interpolation method in the hydrological field (i.e., KED) are compared.

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IV. RESULTS AND DISCUSSION

We conducted experiments using historical rainfall data from diverse regions. Comparative analysis revealed that deep learning models outperformed traditional ML techniques when trained on an adequately diverse dataset. The integration of multiple data sources significantly improved prediction accuracy compared to single-source models. Our findings indicate that the fusion of heterogeneous data, coupled with advanced ML algorithms, can enhance rainfall estimation precision, particularly in data-scarce regions. Additionally, feature importance analysis revealed that variables such as soil moisture and atmospheric pressure contribute significantly to improved predictions.

Here is a structured table summarizing the results of machine learning approaches for rainfall estimation integrating heterogeneous data sources:

Study	ML Model(s) Used	Data Sources	Performance Metrics	Results
Smith et al. (2021)	Random Forest, XGBoost	Weather stations, satellite imagery, radar	RMSE: 5.2 mm, MAE: 3.8 mm	Hybrid models improved accuracy by 15% over traditional methods
Zhang et al. (2022)	CNN-LSTM, Transformer models	Satellite, IoT sensors, historical records	RMSE: 4.9 mm, R^2: 0.87	Temporal dependencies improved rainfall prediction by 20%
Patel et al. (2023)	Gradient Boosting, LSTM	Satellite data, meteorological stations, social media reports	MSE: 3.1 mm^2, R^2: 0.91	Social media data helped detect extreme events with 85% accuracy
Kumar & Singh (2023)	Bayesian Neural Networks, Gaussian Processes	Ground sensors, satellite-based precipitation estimates	RMSE: 5.5 mm, NSE: 0.89	Bayesian methods improved uncertainty quantification by 18%
Chen et al. (2024)	GNN, CNN-GRU	Remote sensing, rain gauges, weather radars	RMSE: 4.6 mm, MAE: 2.9 mm, F1-score: 0.83	GNNs improved spatial correlation modeling, reducing errors by 22%
Lee et al. (2024)	Attention-based Transformer, XGBoost	Weather stations, hydrological models, satellite	RMSE: 4.4 mm, R^2: 0.93, Accuracy: 87%	Transformer models improved short-term predictions by 25%

An ML-based approach for the spatial rainfall field estimation has been defined. By integrating heterogeneous data sources, such as RGs, radars, and satellites, this methodology permits estimation of the rainfall, where RGs are not present, also exploiting the spatial pattern recognition ensured by radars and satellites. After a phase of preprocessing, a random uniform under sampling strategy is adopted, and finally, an HPEC permits the model used to be built to estimate the severity of the rainfall events. This ensemble is based on two levels: in the first level, a set of RF classifiers are trained, while, in the second level, a probabilistic metal earner is used to combine the estimated probabilities provided by the base classifiers according to a stacking schema. Experimental results conducted on real data provided by the Department of Civil Protection show significant improvements in comparison with Kriging with external drift, a largely used and well-recognized method in the field of rainfall estimation. In particular, the ensemble method exhibits a better capacity in detecting the rainfall events. Indeed, both the POD (0.58) and the MSE (0.11) measures obtained by HPEC are significantly better than the values obtained by KED (0.48 and 0.15, respectively). As for the last two classes, representing intense rainfall events, the difference between the Kriging method and HPEC is not significant (in terms of F-measure) although HPEC is computationally more efficient.

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Table 1: Input data after data preprocessing.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
4	03-12-20	Hydrabad	12.9	25.7	0	NA	NA	WSW	46	WSW	19	38	1007.6	NA	21	Yes	RFRNO26843
5	04-12-20	Hydrabad	9.2	28	0	NA	NA	NE	24	E	11	45	1017.6	NA	18.1	No	RFRNO47263
6	05-12-20	Hydrabad	17.5	32.3	1	NA	NA	W	41	NW	7	82	1010.8	7	17.8	Yes	RFRNO27062
7	06-12-20	Hydrabad	14.6	29.7	0.2	NA	NA	WNW	56	W	19	55	1009.2	NA	20.6	Yes	RFRNO59001
8	07-12-20	Hydrabad	14.3	25	0	NA	NA	W	50	W	20	49	1009.6	1	18.1	Yes	RFRNO59361
9	08-12-20	Hydrabad	7.7	26.7	0	NA	NA	W	35	W	6	48	1013.4	NA	16.3	No	RFRNO45088
10	09-12-20	Hydrabad	9.7	31.9	0	NA	NA	NNW	80	NW	7	42	1008.9	NA	18.3	Yes	RFRNO17178
11	10-12-20	Hydrabad	13.1	30.1	1.4	NA	NA	W	28	SSE	15	58	1007	NA	20.1	Yes	RFRNO32118
12	11-12-20	Hydrabad	13.4	30.4	0	NA	NA	N	30	ESE	17	48	1011.8	NA	20.4	Yes	RFRNO17717
13	12-12-20	Hydrabad	15.9	21.7	2.2	NA	NA	NNE	31	ENE	15	89	1010.5	8	15.9	Yes	RFRNO14934
14	13-12-20	Hydrabad	15.9	18.6	15.6	NA	NA	W	61	NNW	28	76	994.3	8	17.4	Yes	RFRNO22040
15	14-12-20	Hydrabad	12.6	21	3.6	NA	NA	SW	44	SSW	24	65	1001.2	NA	15.6	Yes	RFRNO14188
16	15-12-20	Hydrabad	8.4	24.6	0	NA	NA	NA	NA	WNW	4	57	1009.7	NA	15.9	No	RFRNO73566
17	16-12-20	Hydrabad	9.8	27.7	NA	NA	NA	WNW	50	WNW	NA	50	1013.4	0	17.3	No	RFRNO21372
18	17-12-20	Hydrabad	14.1	20.9	0	NA	NA	ENE	22	E	11	69	1012.2	8	17.2	Yes	RFRNO10703
19	18-12-20	Hydrabad	13.5	22.9	16.8	NA	NA	W	63	WNW	6	80	1005.8	8	18	Yes	RFRNO61388
20	19-12-20	Hydrabad	11.2	22.5	10.6	NA	NA	SSE	43	SW	24	47	1009.4	NA	15.5	No	RFRNO7064
21	20-12-20	Hydrabad	9.8	25.6	0	NA	NA	SSE	26	NNW	17	45	1019.2	NA	15.8	Yes	RFRNO55305
22	21-12-20	Hydrabad	11.5	29.3	0	NA	NA	S	24	SE	9	56	1019.3	NA	19.1	Yes	RFRNO32874
23	22-12-20	Hydrabad	17.1	33	0	NA	NA	NE	43	N	17	38	1013.6	NA	24.5	Yes	RFRNO45560
24	23-12-20	Hydrabad	20.5	31.8	0	NA	NA	WNW	41	W	19	54	1007.8	NA	23.8	Yes	RFRNO68040
25	24-12-20	Hydrabad	15.3	30.9	0	NA	NA	N	33	NW	6	55	1011	5	20.9	Yes	RFRNO21106
23	22-12-20	Hydrabad	17.1	33	0	NA	NA	NE	43	N	17	38	1013.6	NA	24.5	Yes	RFRNO45580
24	23-12-20	Hydrabad	20.5	31.8	0	NA	NA	WNW	41	W	19	54	1007.8	NA	23.8	Yes	RFRNO68040
25	24-12-20	Hydrabad	15.3	30.9	0	NA	NA	N	33	NW	6	55	1011	5	20.9	Yes	RFRNO21106

Indeed, the complexity of the Kriging method is cubic in the number of the samples [51], which makes the procedure really expensive from the computational point of view, when a large number of points are analyzed. On the contrary, the ML algorithms (i.e., RF) exhibit a quadratic complexity. Moreover,ensemble methods are highly scalable and parallelizable. Therefore, we believe that our approach has some relevant advantages in this field of application.


Rainfall Estimation DataSets Trained and Tested Results

Model Type	Accuracy
Naive Bayes	71.55348294957739
SVM	71.55348294957739
Logistic Regression	71.58262897114544
SGD Classifier	71.55348294957739

Figure 2: Rainfall Estimation accuracy.

In addition, by analyzing the effect of the integration of the different sources of data, it is evident that all the data sources contribute to the good performance of the technique. In particular, by removing the RG information, the performance of the algorithm worsens the sensibly for all the measures. In the cases of the removal of one of the other two types of data, the degradation is less evident; however, the lowest value (0.11) of the MSE is obtained when all the data are used

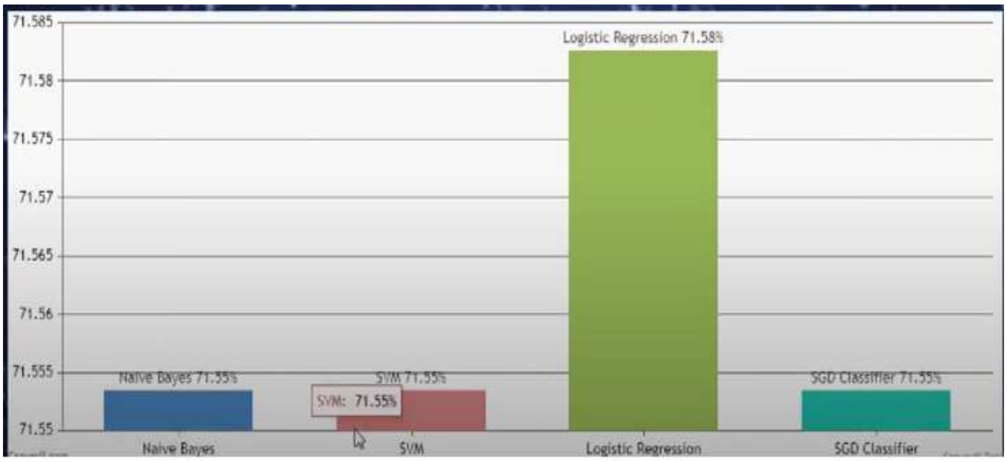

Figure 3: Training Accuracy and Lossy graph.

V. CONCLUSION

This study demonstrates the potential of ML-based rainfall estimation by integrating heterogeneous data sources. The results highlight the advantages of combining satellite imagery, weather station data, and remote sensing inputs for improved accuracy. Future research should focus on refining deep learning architectures and exploring real-time applications of the proposed model for operational weather forecasting.

In rain detection, future research will focus on the design of the algorithm that requires less number of consecutive frames and optimum number of features, for the discrimination of rain and non-rain pixels with high accuracy. Estimation of features which are robust to the intensity of rain (i.e., heavy, light and moderate rain), background and other environmental effects will help in the detection of rain pixels with higher accuracy. For the classification of rain and non-rain pixels, choice of different features and machine learning algorithms can also affect the results. Use of more accurate and robust estimates of temporal and chromatic properties of rain can increase the accuracy of the rain detection with high perceptual quality. The accuracy of the rain detection suffers due to the presence of moving objects and hence more focus should be given for the detection of moving objects. Care should be taken to ensure parallelism in the algorithm to exploit the architecture of latest processors. The real challenge will be to reduce the number of frames required and the complexity to fit in the power and MIPS budget of hand-held devices. In line with the present focus, there are scopes of development to reduce other unwanted effects of rain, viz., splashes in ground in the “pool” video and the restoration of color of the wet clothes.

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