Kanpur	0.0663	0.2575	0.2018	0.0936
Nagpur	0.1946	0.4411	0.2221	0.1748
Pune	0.1213	0.3483	0.1323	0.1414

To be more precise, Fig. 4 shows that while all meteorological elements are associated with rainfall, the effects of the numerous features are not as great as those of the other main features. WindGustKmph, FeelsLikeC, Humidity, CloudCover, and WindChillC are the top five desirable qualities that are most important, in that order. WindSpeedKmph, TempC, Visibility, MaxTempC, and HeatIndexC are the top five unfavourable characteristics that are most important, in that order.

The attribution value and the feature value of the rainfall show a negative/positive association, indicating that a greater value will have an inhibitory influence on the impending rainfall and cause it to be lower/higher. This could be explained by the red hue in Figure 4's SHAP Bee Swarm Plot.

We may better understand how the factors combine to produce the expected target variable by examining the individual SHAP force diagram [11]. The various feature contributions to local level predictions were shown by the SHAP force plots. Three crucial features define force plots. Examples of these include: i) base value, which is the average predicted observation of the test dataset; ii) output value, which is the expected value of each individual observation; and iii) colours, which indicate which variables push the prediction lower and which push the prediction higher, depending on their variable type [6]. Nevertheless, it deviates from the accepted method of analysing SHAP plots due to the presence of both positive and negative values. When the anticipated value is higher than the base value, the prediction is pushed higher by the red colour and lower by the blue colour, and vice versa. As a result, SHAP has been used for each city to interpret the model output for varying rainfall conditions and to comprehend the interactions among variables leading to the model output in Figure 5. Using SHAP force plots, a model explanation was produced for each city.

Variations in the research areas are probably the cause of the discrepancies in certain significant factors that were discovered [6]. The impact of negative features like WindSpeedKmph, Visibility, and MaxTempC and positive features like WindGustKmph, FeelsLikeC, and CloudCover on rainfall forecast is the same across all cities. But Positive feature WindChillC impact negatively in Bombay and Negative features TempC and HeatIndexC impact positively in Bombay and Bengaluru respectively.

V. CONCLUSION

The necessity of a XAI for rainfall prediction was discussed in the study, and the XAI model SHAP, which reveals the global feature contributions to rainfall prediction, was used to further confirm the ML model's operation. The SHAP Bee Swarm Plot and Force Plot have been used to compare the key characteristics of eight distinct cities: Bengulure, Bombay, Delhi, Hyderabad, Jaipur, Kanpur, Nagpur, and Pune. The top five negative features that matter the most are WindSpeedKmph, TemperatureC, Visibility, MaxTempC, and HeatIndexC, in that order; the top five positive features that matter the most are WindGustKmph, FeelsLikeC, Humidity, CloudCover, and WindChillC, in that order.

VI. FUTURE WORK

Going forward, the research will focus on deep learning models such as XGBoost, LightGBM, Bi-LSTM, SVM, CNN, RF, and human-machine interaction. By using the SHAP framework, users will be able to find a way to anticipate rainfall earlier in the upcoming years.

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