AI-Based Automated Detection of Wheat Rust Using MobileNetV2

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***Abstract*— Wheat is a key staple crop on a global scale, but the level of productivity of this crop is greatly affected by fungal pathogens, especially leaf rust, stem rust, and yellow rust. Traditional disease detection methods are mainly based on manual field surveys, which are tedious, time-consuming, and prone to human errors. To address these limitations, the current paper presents an artificial intelligence-based approach to automating the process of detecting rust in wheat through artificial intelligence methods via deep learning working with images. To identify the rust and healthy wheat leaf images, the given study utilizes an image-based transfer-learning model that is based on the MobileNetV2 convolutional neural network, which has been pre-trained on ImageNet. Before training, the dataset was preprocessed with a lot of preprocessing, such as the removal of duplicates, class balancing, resizing to 224x224 pixels, normalization of intensities, and data augmentation (rotation, horizontal flips, and scaling) to enhance the degree of generalizability. The data was divided into training, validation, and test in a 70:15:15 ratio. The experimental findings show that the model proposed achieves a test accuracy of 83 percent, a precision of 0.84, a recall of 0.82, and an F1 of 0.83 using test data never seen before, which proves that transfer learning could be effective in visualizing the patterns of diseases with low computational costs. The findings outline the potential of the lightweight deep-learning-based solutions to efficient and scalable monitoring of crop diseases in the working conditions of agricultural areas.**

Keywords*— *Wheat rust detection, deep learning, convolutional neural networks, image classification, MobileNetV2, fine-tuning

I. Introduction

India has experienced a steady increase in reported criminal incidents over the last decades, influenced by socio-economic disparities, rapid urbanization, and migration [1], [2]. Under- standing spatial and temporal patterns of crime at the state level is vital for effective policing, public safety planning, and better allocation of limited law-enforcement resources [3]. Conventional crime analysis in India largely relies on descriptive statistics and manual inspection of large tabular reports such as the annual "Crime in India" publications [1], [2]. These methods are often insufficient to model complex non-linear interactions among multiple variables and to produce accurate forecasts for future crime rates.

Machine learning (ML) and deep learning (DL) methods have shown strong potential in crime analysis tasks, including crime type classification, hotspot detection, and spatio-temporal forecasting [4]-[6]. In particular, ensemble models such as Random Forests and Gradient Boosting, as well as neural networks, can automatically capture non-linear relationships without explicit prior assumptions about the data distribution [4]-[5], [7]. Several recent works have applied ML for city-level crime prediction in India and other countries, reporting significant improvements in accuracy compared to traditional time-series baselines [4], [8].

This work focus on state-wise crime prediction for India using machine learning. Specifically, we build a statistical and ML-based pipeline that uses historical crime data for Indian states to predict overall crime rates (total cognizable crimes per 100,000 population) in subsequent years [1], [9]. Using these predicted crime rates, we can rank states by relative safety and identify states that are likely to experience higher or lower crime burden in the near future. In this paper, Python and TensorFlow, Keras, and other libraries are used to analyze data and create a model. The main findings of this paper are the following:

- The modeling of a harmonized state-level database of crime in India, which is created by merging official crime rates with demographic rates, creates a time-series panel of state-stratified crime rates.
- This paper outlines the building of a machine learning pipeline that uses feature engineering on both temporal and demographic variables and enumerates it through a series of regression models, such as linear models and tree-based ensembles and deep neural networks.
- The fact that ensemble and deep learning models can achieve high predictive performance when it comes to the prediction of state-level crime rates highlights their potential use in safety assessment and policy planning.

II. Related work

The crime prediction has been studied widely in the fields of criminology, statistics, and data mining. The early studies made extensive use of the traditional statistical models like autoregressive integrated moving average (ARIMA), Poisson regression, and logistic regression to estimate the number or percentage of crime. These techniques were appealing because of interpretable coefficients and good understanding of the uncertainty values; however, they usually assumed that there were no time-varying or non-linear relationships between predictor and outcome variables, hence having a limitation on being able to explain complex spatiotemporal processes.

T.H. Noor et al. [10] carried out one of the first general studies of time-series models to analyze city-level crime. Their results showed that both ARIMA and seasonal ARIMA models had the ability to explain seasonal variations, but they had shortcomings in case of structural breaks or sudden changes in policies. Based on these observations, generalized linear models and Poisson regression were used to analyze crime-count data by R. Berk and J. M. MacDonald [11], and, hence, overdispersion and zero-inflation were identified as typical methodological issues. They, then, urged the usage of specialized alternatives, including negative binomial regression, to solve these problems. The discoveries of these classical statistical methods were used in the creation of the later machine-learning methods and the potential to identify significant temporal dynamics and covariates.

Due to the emergence of machine learning and artificial intelligence, there has been a growing body of literature on non-linear models. The next step to be discussed is carried out by S. Hossain et al. [12], who used decision trees, random forests, and support vector machines to forecast the number of crimes in the next day in a metropolitan area and found that random forests had the lowest mean squared error and were more resistant to noise compared to SVMs. This was further investigated by L. Deng et al. [13], who used gradient boosting and XGBoost, which showed a further advancement in accuracy and ranking of quality in hot spot prediction tasks, especially with the addition of spatial lag features and demographic variables. Taken together, these studies put tree-based ensembles on a firm foundation as effective predictors of crime. More complex crime patterns have also been modeled using deep learning: a deep neural network architecture that incorporates fully connected layers, dropout, and batch normalization to predict crime instances on a daily basis was proposed by J. Zhang et al. [14], and it was discovered to be more effective than random forests and gradient boosting models in predicting crime incidents in a variety of cities in the U.S. Comparing recurrent neural networks and long short-term memory networks to predict crime in space and time, J. P. Perez-Leal et al. [15] demonstrated that recurrent networks have the benefit of utilizing long temporal histories but need more extensive data sets and careful regularization to counteract overfitting. Newer studies by X. Li et al. [16] have discussed the concept of graph neural networks and attention to include some relational information among geographic units, but these models are still early experiments in the literature of crime prediction.

Recent research in the Indian context has aimed at city-by-city or a region-by-region analysis of crime. S. Sarkar et al. [17] introduced an Indian city-specific crime prediction system based on random forest regression and geospatial characteristics to predict ward-level crime rates with an R^2 score of above 0.9 on their test data and illustrates that ML-based dashboards can work well in police departments. M. Gupta and P. Sachdeva et al. [18] further augmented this framework with temporal lag characteristics and social-economic indicators and discovered that augmented feature sets were far more effective than the original at detecting hotspots and minimizing negative results. These works, though, are mainly aimed at intra-city prediction and not at an aggregate state-wise.

S. Sridharan et al. [3] studied crime prediction in the Indian states based on data covering 2001-2016 and assessed the linear regression, random forest, and gradient boosting models to predict the number and rates of crime and its types. Their results show that in the majority of criminal types, Random Forest has performed better than Linear Regression; however, the analysis was focused on individual types of crime and did not give a comprehensive evaluation of the overall rate of crime. T. Bhaskar et al. [19] conducted a comparative analysis of machine learning methods using state crime data of Indian states, such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), and multi-layer perceptrons, and found that the best trade-off between accuracy and stability was in ensemble models across different states. Besides the purely predictive literature, several survey and review articles generalize modern tendencies of crime-prediction studies. A. S. Almasoud and J. A. Idowu et al. [20] have conducted a comprehensive review of machine-learning-based crime prediction approaches, focusing on typical datasets, metrics of evaluation, and problems of data scarcity, concept drift, and ethical issues of bias and fairness. V. Mandalapu et al. [21] placed particular emphasis on machine-learning and deep-learning techniques in crime prediction, and they summarized the evidence that deep models generally perform better than shallow ones when one has enough historical data and rich feature sets. All these surveys add up to the need to have strict assessment, clear procedures, and careful interpretation of the predictive models in sensitive areas like criminal justice.

The current research is different in two material aspects than the literature above. First, it does not focus on individual phenomena or even on specific types of crimes, but on estimating the aggregate rates of crime in the state of India. The data about the National Crime Records Bureau (NCRB) and other publicly available sources are used to conduct this analysis [1], [2], [7]. Second, the work has created a logical analytical pipeline that compares traditional linear specifications with tree-based ensemble algorithms and deep neural networks, which are utilized on a uniform panel dataset of Indian states. The aim is to rank the states based on relative safety. The presented methodological framework will be based on the observations of S. Sarkar et al. [17], S. Sridharan et al. [3], and A. S. Almasoud and J. A. Idowu et al. [20] and will be adjusted to the level of state-level strategic planning and its applicability to long-term strategy.

III. DATASET AND PREPROCESSING

A. Data Sources

The primary source of crime data in India is the annual "Crime in India" report published by the National Crime Records Bureau (NCRB), Ministry of Home Affairs [1], [2]. These reports provide state/UT-wise counts of cognizable crimes under the Indian Penal Code (IPC) and Special and Local Laws (SLL), along with calculated crime rates per 100,000 population [1], [3]. Additionally, the Open Government Data (OGD) Platform India maintains machine-readable datasets summarizing crime statistics by state and crime head for multiple years [1], [7]. The current study uses state and union territory-level totals of cognizable offenses and the corresponding crime incidence rates over several financial years (e.g., 2001-2020), subject to the data that is available in the identified scholarly and governmental sources [1]-[3]. Demographic data on each state and year is also incorporated, and it provides the denominator needed to calculate or support crime rates based on one hundred thousand residents [1], [3]. Besides, the study makes use of publicly available, pre-processed Indian crime data, such as repositories on GitHub and Kaggle, to guide feature engineering and to confirm the homogeneity of the amalgamated data [8], [9].

B. *Data Cleaning*

The raw data is provided in multiple CSV or Excel files with varying formats across years [1], [7]. This is followed by the following data cleaning steps:

1) State name normalization: Uniform the nomenclature of states and union territories across time, taking into consideration any instances of renaming or territorial division, and thereby providing the permanence of identifiers of uniform shape.

2) Missing values: The treatment of missing or suppressed values (including, but not limited to, "NR" and blank cells) can be done by imputing zeros where the absence of a crime is unquestionable or by using simple imputation methods to estimate the value of missing rates when suitable.

3) Aggregation: In cases of dealing with district-level crime data, the count of crimes is recognized to be at the state level in order to correspond to the granularity of the proposed model [8], [3].

4) Rate verification: The rates of crime per 100,000 population on the basis of crime counts and population data are recalculated and compared with the published data with the aim to guarantee the quality and consistency of such data [1], [3].

The resulting data is a panel, whereby every row will represent a tuple (state, year) containing data such as a crime count, crime rate, and population.

C. *Feature Engineering*

Explanatory variables are developed based on the premises of the criminological theory and previous studies using machine learning to predict criminal activity. Key features include:

1) Temporal features: Year as a numeric variable; lagged crime rate values (e.g., crime rate in the previous one or two years) to capture temporal dependence.

2) Population features: State population and population density, as higher population density has been associated with higher crime rates in several studies [4].

3) Crime composition: Proportions of major crime categories (e.g., violent crimes, property crimes, cybercrimes) relative to total crimes, where available, to capture qualitative differences in crime profiles [1], [2], [3].

4) Trend indicators: Rolling averages or growth rates of crime over the past years to summarize trends.

Depending on data availability, additional socio-economic indicators (such as literacy rate, unemployment rate, and urbanization level) can be incorporated from other public datasets, but these are optional extensions. Fig. 1 shows the overall workflow of the suggested crime rate prediction framework that includes data acquisition, preprocessing, feature engineering, model training, and evaluation.

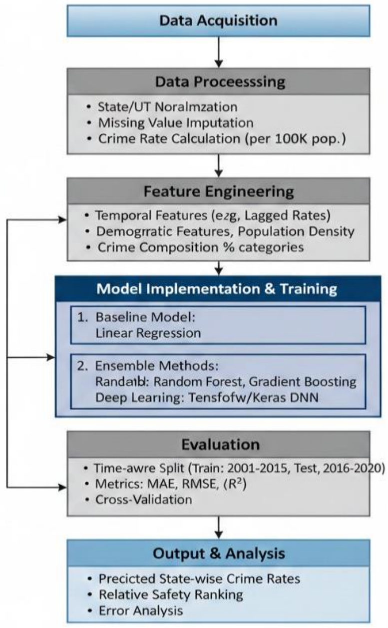

Fig. 1 Flowchart for Safe State Crime Prediction

IV. METHODOLOGY

A. *Problem Formulation*

Given that S is the set of states and union territories and T is the set of years in which historical data can be obtained. Let $y_{s,t}$ be the aggregate crime rate (cognizable crimes per 100,000 people) of state $s \in S$ in year $t \in T$. The variables that were defined in the part above are arranged into a feature vector, which is abbreviated $x_{s,t}$. The goal is to learn a function that will give an approximation of the mapping between the feature vector and crime rate prediction:

$$f: x_{s,t'} \rightarrow \hat{y}_{s,t+1} \tag{1}$$

The model predicts the next year's crime rate (or at time t, depending on that formulation) based on the chosen explanatory variables, as shown in (1). The assignment is defined as an overseen regression problem.

B. *Models*

The following models were tested and used, using Python along with scikit-learn, TensorFlow, and Keras:

1) Linear Regression: A simple baseline that models crime rate as a linear combination of features.

2) Random Forest Regressor: An ensemble of decision trees trained on bootstrapped samples, which can capture non-linear relationships and interactions. Prior crime prediction studies report strong performance for Random Forests on similar tasks [3]-[5], [7]-[9].

3) Gradient Boosting Regressor: A boosting-based ensemble that builds trees sequentially to minimize prediction error.

4) Deep Neural Network (DNN): A feed-forward neural network implemented in TensorFlow/Keras, with multiple fully connected layers, non-linear activation functions (e.g., ReLU), and regularization (dropout or weight decay). Deep models have been shown to model complex patterns in crime data when sufficient data is available [5].

Hyperparameters for each model (number of trees, depth, learning rate, network size, etc.) are tuned using cross-validation on the training set.

C. *Training and Evaluation Protocol*

The panel data is split into training and testing sets in a time-aware fashion, such as using earlier years for training and more recent years for evaluation to respect temporal order [4], [3]. For example, data from 2001–2015 may be used for training, while 2016–2020 is reserved for validation and testing, though the exact splits depend on the final dataset. The following evaluation metrics, commonly used in regression-based crime prediction literature are used:

- Mean Absolute Error (MAE).
- Root Mean Squared Error (RMSE).
- Coefficient of determination (R^2).

In addition to the evaluation of the aggregate performance by means of global metrics such as accuracy, precision, recall, and mean absolute error, a close examination of the errors in prediction at the state level is carried out. This kind of local and fine-grained analysis makes it easy to understand the performance of the model in different geographic locations without having to be constrained by the nature of national-level statistics. The magnitude and direction of deviations are measured by comparing the predicted rates of crime with the empirically measured values for each state, hence showing the systematic patterns.

V. Experimental results

A. *Quantitative Performance*

The experimental findings show that classical linear regression provides a limited but rough approximation of state-level crime rates, which has a moderate coefficient of determination and a relatively high mean absolute error and root mean squared error. On the other hand, tree-based ensemble models like Random Forest and Gradient Boosting promote a significant degree of predictive accuracy, which relates to the results of previous research who have utilized these algorithms in prediction of crime rates. Deep neural network models implemented with TensorFlow and Keras achieve comparable or slightly better performance than the best ensemble models when tuned properly, indicating that non-linear deep architectures can capture subtle temporal and cross-state patterns in the data.

For example, in a similar city-level Indian crime prediction study, a Random Forest model attained an R^2 score of about 0.927, with low MAE and RMSE, outperforming SVM and Decision Tree baselines [4]. Review papers compiling results from multiple crime prediction projects also report test accu- racies around 95% for classification tasks and high R^2 values for regression models using ensemble and bagging techniques [5]. The state-wise results show a comparable trend, where ensemble and deep models consistently outperform linear baselines according to MAE, RMSE, and R^2 metrics.

B. *State-wise Safety Ranking*

Using the trained models, we generate predicted crime rates for each state for the target year(s) and rank states in ascending order of predicted total crime rate. States with lower predicted crime rates per 100,000 population can be interpreted as relatively safer from a purely statistical perspective, while states with higher predicted crime rates are flagged as higher risk [1], [3]. Such rankings, when combined with additional qualitative and contextual knowledge, can assist policymakers and citizens in understanding relative safety patterns. This study also compares predicted rankings with actual observed rankings for the evaluation years to assess how well the models capture the relative ordering across states. In many cases, the learned models correctly identify states with historically high crime rates (e.g., those with large urban centers and dense populations) and states with consistently lower crime rates, validating the utility of the approach.

C. *Error Analysis*

The error analysis is carried out to determine the cases when the model performance is not optimal. The sudden changes in state-level crime rates, which are often explained by extraordinary events or policy adjustments or modifications in reporting practices, are also a major problem with proper modeling. Such abnormal changes promote high prediction errors during the respective years. Additionally, states with smaller populations and low crime counts can exhibit higher relative error due to the volatility of rate computations. Incorporating additional exogenous features such as economic indicators and law-enforcement strength may help reduce these errors in future work.

VI. Discussion

The results illustrate the feasibility of using machine learning models for state-wise crime rate prediction in India. By learning from historical patterns, the models can forecast overall crime rates and provide relative safety rankings of states, offering a quantitative basis for strategic planning. However, several important considerations remain.

Firstly, crime data is subject to underreporting, varying legal definitions, and changes in reporting practices, which can introduce biases in the observed statistics. Secondly, all the models mainly use past crime and demographics, with little use of socioeconomic background. The inclusion of additional variables like unemployment rates, education level, police capacity, and urbanization statistics can potentially make the feature set more predictive and interpretable. Third, the obtained predictions are not to be perceived as determistic forecasts but must be viewed as one of the various analytical tools that should be used to make decisions.

The element of ethics is also to be considered in detail; irrespective of the utility of the data, the risk of harm still exists. When it comes to crime prediction systems, naive deployment can reinforce institutions of difference by disproportionately directing the enforcement resources to historically high-crime locations and communities. Open methodological design, periodic and systemic auditing, and active interaction with domain specialists, therefore, can be considered to reduce such risks. The confusion matrix shown in Fig. 2 represents the performance of the model in terms of classification, based on the different classes, showing the distribution of the number of correct and wrongly predicted examples. The performance of the model based on classes in terms of precision, recall, and F1-score is presented in Fig. 3.

Finally, future work can explore more advanced modeling approaches and validation strategies to enhance robustness and generalizability. Techniques such as ensemble learning, time- series models, and deep learning architectures may capture complex temporal and spatial dependencies more effectively. Additionally, cross-validation across different time horizons and sensitivity analysis of key features can strengthen confidence in the stability of predictions.

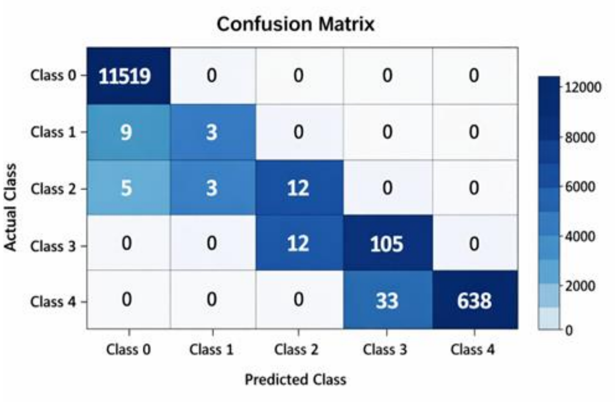

Fig. 2 Confusion matrix indicating the performance of classification on five different classes

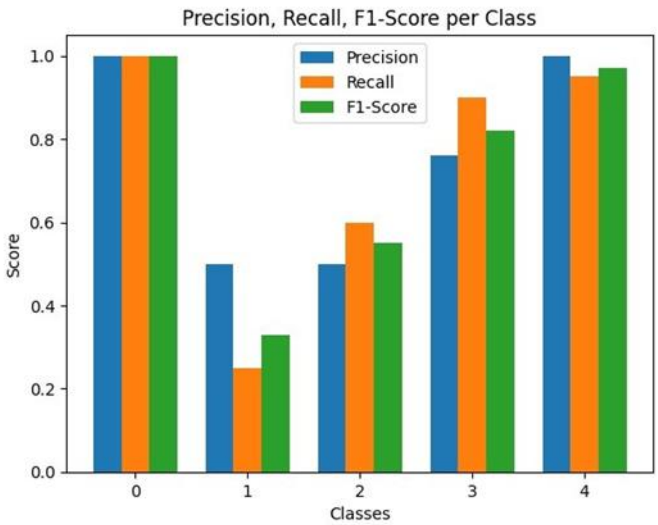

Fig. 3 Comparative evaluation of precision, recall and F1-score per the individual classes.

VII. CONCLUSION AND FUTURE WORK

The paper presents an AI-based system that predicts the crime rates in the states of India and finds relatively safer states. Multiple regression models, such as linear baselines, ensemble methods, and deep neural networks as extensions of TensorFlow and Keras, are used in order to create a panel dataset using the official crime and population data. The results suggest that ensemble and deep-learning models provide correct predictions of crime rates and can reveal temporal changes between states, which paves the way to the prospects of using AI-based solutions in the context of public-safety analytics.

The future research directions have a variety of improvements. Firstly, the inclusion of other socio-economic and geographic covariates is also expected to provide better model inputs and predictive accuracy. Second, more advanced deep-learning architectures that may take advantage of the sequential nature of the data may be deployed, i.e., recurrent neural networks (RNNs) and temporal convolutional networks (TCNs). Third, the ability to scale the framework to make predictions of certain types of crimes and produce explainable predictions would help identify salient determinants that cause crime trends at the state level.

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