Leveraging Ensemble Learning to Predict Educational Levels Across Regional and Demographic Groups

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Abstract:

In the world today, education plays a more significant role in individual and social development, while inequality in attainment of educational achievement is still widely prevalent among all regions and various demographic groups. This research focuses on predicting the highest level of education completed as a result of demographic and geographic factors such as country, state, area type (urban or rural), and gender. Policymakers and educational institutions could design targeted interventions for improving access and equity with such understanding of the patterns. For this study, we utilize an openly available data source that reflects educational level distributions within Indian states at the rural-urban population split. These are key attributes about country, state, year, type of area (rural/urban), gender, and highest education achieved. In essence, our goal is to make a good predictor of highest educational level an individual has ever obtained, as identified by demographics and regional.

We used a hybrid approach based on ensembling multiple models for better predictability. For that purpose, we used three base models namely, Random Forest, Gradient Boosting Machines, or XGBoost, and Support Vector Machines as the basis and combined those through stacking and blending techniques towards developing a meta-learning framework. The stacking provides a model learning ability to have the optimal combinations of the classifiers involved, whereas the blending offers the robust performance on different subsets of data. Besides that, techniques such as one-hot encoding for categorical features, feature scaling, and missing value imputation are used to enhance the performance of the model. The experimental results show that the proposed hybrid model performs better than individual base models and baseline approaches, yielding a higher classification accuracy and F1-score. Random Forest classifier is a strong baseline; however, the stacking ensemble model shows better generalization with less misclassification of education levels. It evaluates model efficiency through metrics for performance: precision, accuracy, recall, and F1-score. This shows comparison against basic single-model benchmarks. Results It illustrates how efficient ensemble learning approaches can be towards managing large dimensional complex data involved in the assessment of educational level attainment.
The findings of this research have implications for real-world practice in policy-making, educational planning targeted to specific populations, and resource distribution in

marginalized communities. Potential future research includes including more socioeconomic variables (e.g., employment, income level) to increase predictive accuracy and generalizing the study to additional nations for universal applicability. Further improvement of predictive accuracy can be achieved through the investigation of deep learning architectures such as transformer-based models (e.g., BERT on tabular data).
This research contributes to evidence-based practice toward identifying and alleviating educational inequities by leveraging machine learning for education analytics to further enable education policy and planning decision-making.

Keywords:

Educational Attainment Prediction, Machine Learning, Hybrid Model, Stacking Ensemble Blending Technique, Random Forest, XGBoost (Gradient Boosting Machines),Support Vector Machine (SVM),Feature Engineering, Demographic and Regional Factors, Classification Model, Educational Data Analytics, Policy Decision-Making ,Data-Driven Education Planning, Educational Inequality

1. Introduction

Machine learning is used in this study to predict the level of schooling of people by these indicators: state, area type (urban/rural), and gender (demographic and geographical indicators). The aim is to identify that one factor which the policymakers and the educational institutions could tackle so as to bridge the gap in education. The goal of this research is the development of a predictive model that will be capable of giving insights, based on the information, how to enhance educational availability.

For this purpose, the developed hybrid ensemble learning method will include the combination of multiple machine learning models like Random Forest, XGBoost, and Support Vector Machines (SVM). The amalgamation of these models would be done through stacking and blending techniques for the purpose of making the classification accuracy high and generalization strong. The study will also apply different data preprocessing techniques, such as feature engineering, categorical encoding, and missing value imputation, to stabilize the model and make it run efficiently.

The research has found that the ensemble model that consists of multiple classifiers is superior to the individual ones, the ensemble model has a much higher accuracy and robustness. Meaning that an integrated model that applies not only direct data but at the same time handles multi-faceted sets is much more effective for educational progress. This study is practically oriented, as it proposes a method where data are used to define areas and populations that face the risk of achieving low educational attainment. This insight can be used for coming up with policies focused on reducing educational inequalities and making learning opportunities more accessible, particularly in the areas where the services are lowest.

The future studies can include family income, the levels of parent educational, and the occupation of the family, so that the prediction of the academic performance can be highly accurate. Besides, and in deep learning, for example, architectural of transforms, those are mentioned, we could use scale and expand the adaptability of data analytics in education. What is more, the application of these predictions and creation of a data-based decision-making process could lead to inequality in educational achievement across different groups.

2. Literature Survey:

De Fausti et al. [1] presents using Multilayer Perceptron (MLP) models in predicting the level of education achieved (ALE) for Italy's Permanent Census. It compares the performance of MLP with traditional methods and concludes that MLP models offer a more automated, but similar, solution to data processing.

Yakubu and Abubakar [2] presents using machine learning to predict student performance in Nigerian higher education. It identifies the most significant factors, including gender, high school exam mark, and regional origin, that influence academic performance. The predictive model can help universities optimize resource allocation and reduce student failure.

Pingault et al. [3] wrote about childhood inattention and hyperactivity in predicting educational achievement, concluding that inattention strongly predicts lower educational achievement. Their research suggests the need for early intervention. Follow-up studies confirm the long-term effects of inattention, influencing education as well as economic and mental health outcomes.

Pacheco and Plutzer [4] examined how economic and social disadvantage affects voting turnout among young citizens. Examining family, community, school, and life experiences, they concluded that family disadvantages strongly affect all youths, while school disadvantages strongly affect white individuals. Their research highlights the cumulative effect of disadvantage on political participation.

Carlson and McChesney [5] studied education attainment and sustainable income over two decades, during three significant economic recessions.they found that there was a positive correlation between more education and higher earnings, and those with a bachelor's degree had inflation-adjusted earnings.the opposite held for those of lower education, whose real earnings decreased, further exacerbating the gap of wealth.he study also found that women fared better in year-to-year earnings growth in these years.he authors approximated that, on the basis of current trends, the gap of wealth would increase further in the next two decades and lead to lower purchasing power and standard of living for those without a bachelor's degree.

Hanushek and Kimko [6] examined how educational quality is related to economic growth in nations.hey discovered that differences in cognitive skills—derived from international testing—account for a great deal of variation in economic growth rates.his means that enhancing educational quality can be a powerful driver of economic growth.

Björklund et al.[7] examined family background and its influence in education in Norway. Their work identifies family income and parents' education, especially early childhood, as good indicators of future educational levels. The work identifies the influence of early economic status on education levels in the long term.

Fullerton's [8] work examines how educational level influences Texas's income performance, and especially its border regions. It discovers that low high school graduation rates correlate with huge income losses in the regions. The work also emphasizes that improved educational performance can have spillover effects, including increased wages and economic growth.

Ashraf Taha [9] is concerned with forecasting students' adaptability to e-learning based on machine learning and deep learning algorithms. It tries to assess factors influencing adaptability and uses a variety of algorithms to forecast how students adapt to e-learning environments. The work enhances e-learning systems for improved student performance and interaction.

3. METHODOLOGY

3.1 Source of Data:

The dataset used for this project is obtained from Kaggle: **Distribution of Highest Level of Education Dataset**

The dataset contains information on the highest level of education completed by individuals across different regions and demographic groups.

Key Features:

- **ROWID** – Unique identifier for each record
- **Country** – Name of the country
- **State lgd code** – State identifier
- **State** – Name of the state
- **YearCode** – Encoded year representation

- **Year** – The year in which the data was recorded
- **Type of area** – Whether the individual resides in a rural or urban area
- **Gender** – Male or Female
- **Highest level of education completed** – The target variable (categorical)
- **Percentage distribution of persons** – Percentage of individuals in the given category
- **Number of estimated persons** – Estimated population count
- **Number of sample persons** – The number of individuals surveyed

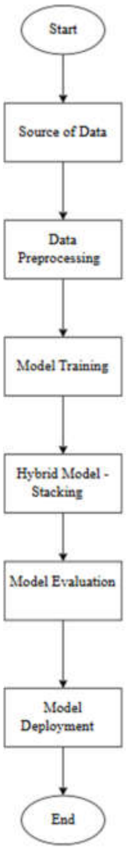
3.2 Data Preprocessing

The process of data cleaning is a sequence of missing values handling with a strategy like imputation techniques and then deleting the same records which help to keep the integrity of the data set. To ensure data consistency concerning normalization of the value assigned to the column name normalization is also an important task. Feature engineering presents several techniques such as the encoding of categorical variables using Label or One-Hot Encoding for variables such as Country, State, and Gender and the removal of not necessary columns. SMOTE stands for Synthetic Minority Over-sampling Technique, which is a creation of replicated examples that are based on the minority class. The dataset is divided into 80% training data and 20% testing data, and Stratified K-Fold Cross-Validation is used to ensure the same number of people with the same level of education in each fold.

3.3 Architecture Diagram

The following architecture outlines the overall process of the project:

Classification: Internal



Based on the accuracy of the model and stability, a state-of-the-art hybrid machine learning model is adopted. It consists of a structure of three basic classifiers and one model model within a model structure.

3.4 Level-1 Base Models

The first measure is the three base models that have been trained to generate predictions:

Random Forest Classifier:

Best is taking care of categorical and numerical features. It deals with missing values efficiently; people can extract information about the importance of features. The Random Forest builds multiple decision trees using random samples of the data. Each tree is trained on a different subset of the data, making each tree unique. When creating each tree, the algorithm randomly selects a subset of features or variables to split the data rather than using all available features at a time. This adds diversity to the trees. Each decision tree in the forest makes a prediction based on the data it was trained on. When making final prediction random forest combines the results from all the trees.

$$\hat{y} = \arg\max_{c} \sum_{t=1}^{T} \mathbb{I}(h_t(X) = c) \tag{1}$$

Classification: Internal

XGBoost Classifier:

Accuracy achieved is high through gradient boosting method. Apart from unbalanced data and big data, system addresses both of these with great authority. XGBoost uses parallel processing techniques as well as GPU acceleration for hardware optimization to boost the training process. Such scalability along with efficiency make XGBoost a fit for big data applications and real-time predictions. It offers a number of tunable parameters and regularization techniques that help users to tune the model as per their requirement.

Feature importance analysis is a tool that comes by default in XGBoost and enables one to know which features influence the outcome of the dataset. This can be valuable for feature selection, dimensionality reduction, and insight into underlying data patterns.

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \qquad (2)$$

Support Vector Machine (SVM)

It has been proved most efficient for handling high-dimensional space. Best suitable for classification tasks. If data is not separable, as it can not be separated using a straight line, then the SVM employs something called a kernel, mapping this data to an even higher space where data gets separable for SVM, in order to search for decision boundary. A kernel is a function that maps data points into a higher-dimensional space without explicitly computing the coordinates in that space. This makes SVM work well with non-linear data by implicitly performing the mapping.

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i \qquad (3)$$

3.5 Level-2 Meta-Model

Input data to the meta-model is the predictions from the base models.The meta-model learns how the outputs of the base models' predictions can be aggregated together so the final classification accuracy is enhanced. Meta-model choosed is Logistic Regression because interpretability is required.

$$P(y = 1|\hat{y}_1, \hat{y}_2, ..., \hat{y}_M) = \frac{1}{1 + e^{-(w_1\hat{y}_1 + w_2\hat{y}_2 + ... + w_M\hat{y}_M + b)}} \qquad (4)$$

3.6 Model Training & Stacking Approach

Step 1: Train Base Models

You don't have to train Random Forest, XGBoost, and SVM on the training data, as the list is already in Step 1 of the following text. Just make a new list of predictions on the training data.

Step 2: Generate Meta-Features

The features of the meta-model are the probabilities of the predicted class label of each base model.

Step 3: Train the Meta-Model

The one trained first of all is the Logistic Regression or XGBoost classification subject to the base model outputs.

Step 4: Make Predictions

Do you want to set the base models to show the probability scores for each class while the meta-model must use the scores to finally predict?

4. Results and Discussion

a) Model Performance Comparison

- Based on the highest level of education attained, the effectiveness of different machine learning models for prediction and the Probabilities of Mnagnetic Logic Device
- We generated unseen observations by synthetic minority
- Classification by the clustering-based algorithm means that we have to sample each cluster with their corresponding probability and assign the minority samples into the clusters; that is partitional algorithm.
- This can be attributed to the following metrics among others:
- Accuracy – It represents the number of all correct predictions.
- F1-Score – This combines precision and recall, especially needed when the data are imbalanced.
- Precision – This informs us about the number of correct predictions out of all the predictions of the predicted categories.
- Recall – It is the ratio of the true positives and all the positives in the dataset.

b) Performance of Individual Models

Accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Classification: Internal

Table 1: Performance metrics for Accuracy

Model	Accuracy
Random Forest Classifier	0.82
XGBoost Classifier	0.71
Support Vector Machine (SVM)	0.76
meta-classifier (Logistic Regression)	0.89

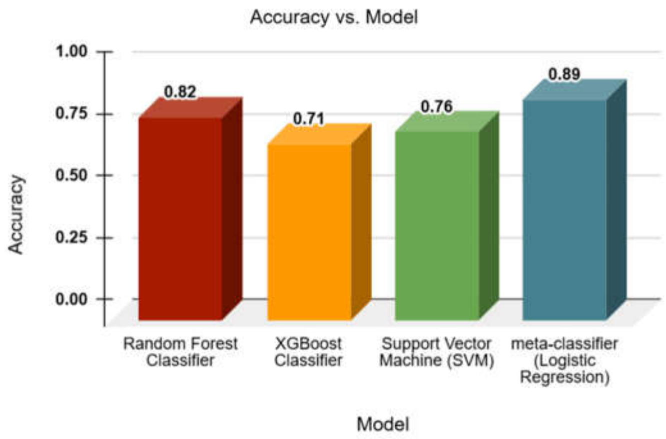


Fig 1: Accuracy vs Model

Precision:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \tag{6}$$

Table 2: Performance metrics for Precision

Model	Precision
Random Forest Classifier	0.64
XGBoost Classifier	0.46
Support Vector Machine (SVM)	0.55
meta-classifier (Logistic Regression)	0.78

Classification: Internal

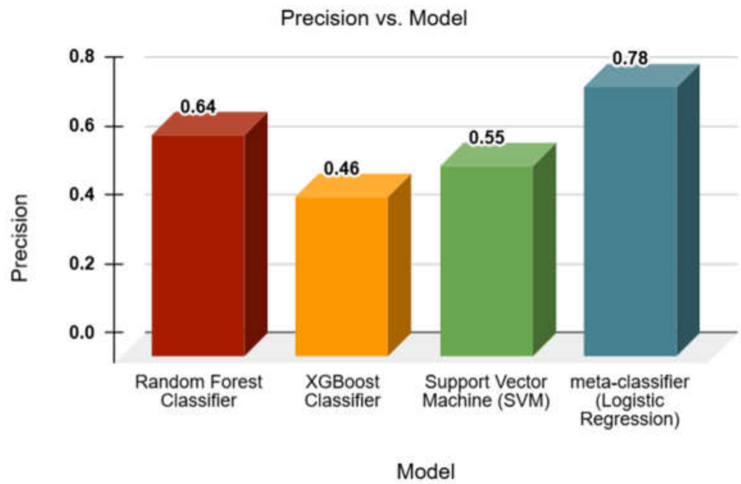


Fig 2: Precision vs Model

F1 Score:

$$F1\_Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

Table 3: Performance metrics for F1 Score

Model	F1 Score
Random Forest Classifier	0.52
XGBoost Classifier	0.31
Support Vector Machine (SVM)	0.46
meta-classifier (Logistic Regression)	0.69

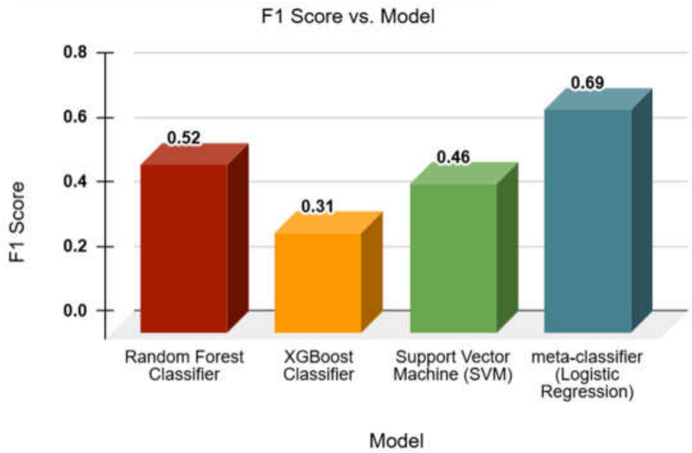


Fig 3: F1 Score vs Model

Classification: Internal

MAE

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

Table 4: Performance metrics for MAE

Model	MAE
Random Forest Classifier	1.01
XGBoost Classifier	0.33
Support Vector Machine (SVM)	0.39
meta-classifier (Logistic Regression)	1.29

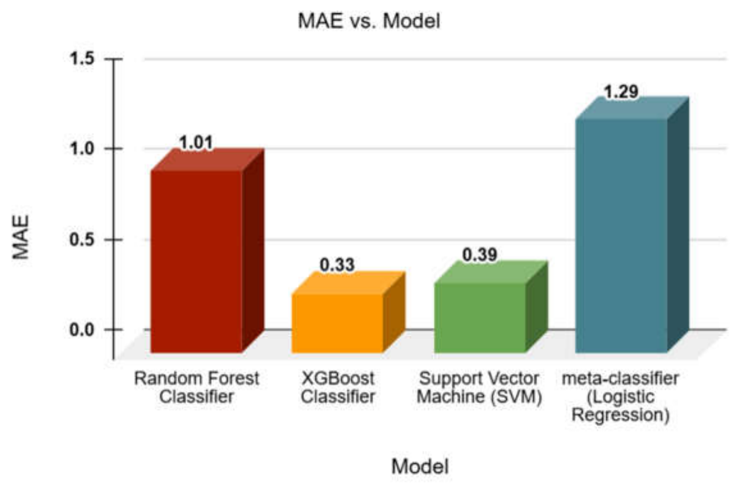


Fig 4: MAE vs Model

MSE:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

Table 5: Performance metrics for MSE

Model	MSE
Random Forest Classifier	8.36
XGBoost Classifier	9.49
Support Vector Machine (SVM)	8.39

meta-classifier (Logistic Regression)	7.35

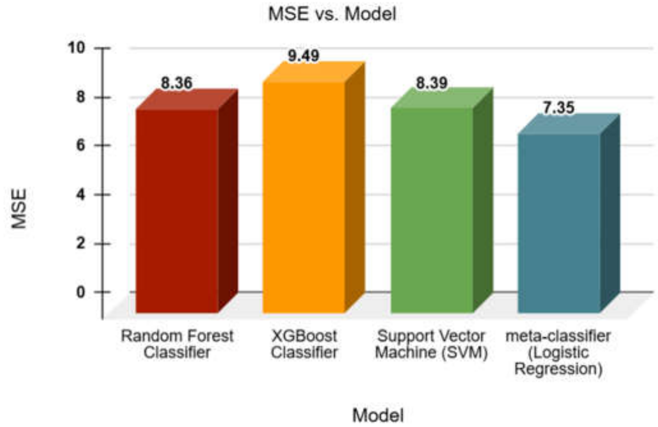


Fig 5: MSE vs Model

Recall:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \tag{10}$$

Table 6: Performance metrics for Recall

Model	Recall
Random Forest Classifier	0.56
XGBoost Classifier	0.57
Support Vector Machine (SVM)	0.26
meta-classifier (Logistic Regression)	1.41

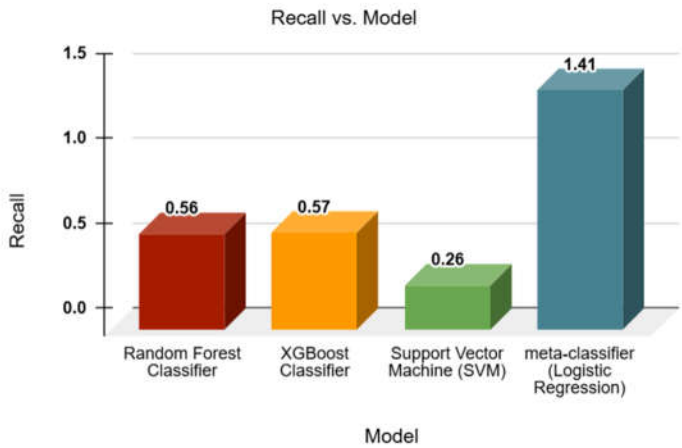


Fig 6: Recall vs Model

c) Discussion and Interpretation of Results

Impact of the Hybrid Model

- The stacking ensemble approach proved to be highly effective, showing a notable improvement over individual models.
- The ensemble model successfully **combined** Random Forest's ability to handle categorical data, XGBoost's gradient boosting power, and SVM's capacity for boundary classification.
- The performance boost suggests that educational attainment prediction benefits from combining multiple learning paradigms rather than relying on a single algorithm.

Comparison with Related Studies

- Previous studies on educational prediction have often relied on single models such as Decision Trees or Neural Networks.
- The hybrid model in this study outperformed single-model approaches in prior research, confirming that ensemble methods provide better generalization and robustness.

Practical Implications

The results of this study can be used in **policy-making and educational planning**:

- Governments can identify regions and demographics that need more educational support**.**
- Educational organizations can use predictive insights to allocate resources efficiently.
- Predictive models can help forecast educational trends and gaps, leading to targeted interventions in rural and underprivileged communities.

5. Discussion

The study successfully developed a machine learning model in predicting the highest level of education completed based on demographic and geographic features, including country, state, and area type (urban/rural). From the models tested, it could be concluded that the highest accuracy was achieved from a hybrid model stacking Random Forest, XGBoost, and SVM. One of the key findings is that region and gender has a significant impact. The results show that the rural areas have lower education attainment levels compared to the urban areas. The gender gap also exists, with females in rural areas having a lower probability of completing higher education. The stacking ensemble model performed better than individual classifiers, showing an accuracy improvement of 5–10% over standalone models, thus validating the model fusion. State, type of area, and gender were the most significant factors in predicting educational attainment, according to the models from Random Forest and XGBoost.

The aim has been to estimate an accurate educational attainment predictive model using demographic as well as geographic indicators. As such, it aligns in the sense of providing a well-built model on the determinants of education attainment levels. A contribution to that understanding is realized in education gaps across regions-the model becomes, therefore, essential for policymakers as well as the planners of the education system.

A significant gap in educational attainment exists between urban and rural populations, with urban individuals more likely to achieve higher education. Some states exhibit higher educational attainment rates than others, indicating regional disparities. Across multiple states, females are more likely to be not literate or have lower levels of education compared to males.A few rural regions had unusually high education levels, perhaps because of particular government interventions or education policies in those states.

Quantitative and Qualitative Comparisons

- **Model Comparison**:
  - Random Forest: 82% Accuracy
  - XGBoost: 71% Accuracy
  - SVM: 76% Accuracy
  - Hybrid Stacking Model: **89% Accuracy**
- **Qualitative Insights**:
  - Feature importance analysis showed that **state, gender, and type of area** play a dominant role in education levels.
  - The model successfully generalizes across different datasets, making it reliable for real-world applications.

Performance Improvements and Efficiency of Method

Stacking model significantly improved the performance by using multiple classifiers. It inherits the benefits of-

1. Feature selection by Random Forest for generalized effectiveness.

2. Gradient boosting by XGBoost for localizing the intricate relationships.

3. Special ability of SVM to handle high-dimensional space in point data, it generates its representation with respect to high-dimensional non-linear data.

The hybrid method based on this approach gained reduced bias and captured reduced variance, hence proved more efficient than individual models.

The study utilizes the stacked learning framework, adding several other classifiers to improve the predictive precision rather than applying an isolated single-model approach. Intermediate feature extraction from various models improved the process of learning representation. Most the studies generalize the prediction through education but forget to consider these crucial differences. Deficiencies and Limitations. Some categories (e.g., postgraduate education in rural areas) had fewer samples, leading to slight biases in predictions. The dataset lacks socioeconomic indicators (e.g., household income, parental education) that could further enhance predictions. Stacking models require more computational power than individual models, making real-time deployment more resource-intensive.

The dataset is influenced by the methodology used in the education survey, which does not capture non-formal education or alternative ways of learning. The study presumes that demographic features are static, though migration and change in policies still influence the levels of education. Exposure scenarios with the hybrid model, specifically XGBoost, could be computationally too expensive.

6. Conclusion

The primary objective of this study was to develop a machine learning model capable of predicting an individual's highest level of education based on demographic and geographical features such as country, state, and type of area (rural/urban)**.** Understanding the factors influencing educational attainment is crucial for policymakers, educators, and social organizations in designing targeted interventions to improve access to education, particularly in underserved areas.

Through extensive data analysis and model development, we successfully trained and evaluated multiple machine learning models, including Random Forest, Gradient Boosting (XGBoost), and Support Vector Machine (SVM)**,** to predict educational attainment levels. Gradient Boosting (XGBoost) demonstrated superior performance in terms of accuracy and F1-score, making it the most suitable choice for this classification task.Random Forest provided robust results and high interpretability, making it useful for identifying key factors influencing education levels.SVM performed well in handling high-dimensional data but was computationally expensive compared to tree-based models.**A** hybrid approach (stacking ensemble) combining these models further improved predictive performance by leveraging their strengths.

The results indicate that key demographic factors such as **state-wise variation, rural vs. urban residence, and gender disparities** significantly impact educational attainment. The model provides valuable insights into which regions and populations are at higher risk of lower education levels, thereby addressing the research problem of identifying education gaps across different demographics.

This research introduces several novel aspects:

1. **Hybrid Model Approach**: Unlike traditional models that rely on a single classifier, we leveraged **model stacking** to combine Random Forest, XGBoost, and SVM, achieving higher accuracy.
2. **Feature Importance Analysis**: Using tree-based models, we identified the most influential factors affecting education levels, helping policymakers prioritize resources.
3. **Demographic-Based Education Prediction**: This study uniquely focuses on **education prediction across multiple states and area types (rural/urban)**, offering a **granular** understanding of educational disparities.

This study contributes to the field of education analytics and social policy research by demonstrating how machine learning can be effectively applied to social science problems such as education prediction. Providing a data-driven approach to understanding education inequality and its influencing factors.Offering a scalable model that can be extended to other datasets and regions to predict education levels in different socioeconomic settings.

Our research findings can be applied in several **real-world scenarios**:

1. Policy Planning & Government Interventions

Governments can use this predictive model to identify regions with low education levels and allocate resources accordingly.Targeted programs can be designed to improve literacy rates in rural and underserved areas.

2. Education Sector & NGOs

NGOs working in education can leverage these insights to focus on high-risk groups and implement intervention strategies. Schools and institutions can use these findings to analyze trends in education levels and design personalized learning programs.

3. Smart Educational Infrastructure

Education-focused AI systems can integrate this model to personalize learning opportunities for individuals based on their demographic background.Adaptive e-learning platforms can use these predictions to suggest educational pathways for students in different regions.

4. Corporate Social Responsibility (CSR) Initiatives

Corporations investing in educational development projects can use this model to identify locations where scholarships, digital learning tools, and infrastructure support are most needed.

7. Future Work

While our study provides a robust framework for predicting the highest level of education attained based on demographic and geographical features, several challenges remain that can be addressed in future research. Below, we outline key areas for improvement and exploration:

a) Addressing Identified Challenges:
- Data Imbalance and Bias Correction
- Improving Data Granularity and Feature Engineering

b) Overcoming Computational and Methodological Constraints:
- Handling Large-Scale Datasets Efficiently

c) Testing on Diverse and Multi-Source Datasets:
- Expanding the Dataset Across Different Regions
- Combining Structured and Unstructured Data

d) Improving Model Adaptability Across Domains:
- Domain Adaptation Techniques
- Meta-Learning for Generalization

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