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Predict Migration Using Machine Learning

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Abstract

Migration prediction plays a crucial role in understanding global movement patterns and assisting policymakers in planning for demographic changes. This project aims to analyze historical migration data and predict future migration trends based on various factors such as country, citizenship, and year. The application uses machine learning models to provide accurate predictions by identifying patterns in migration data. The GUI enables users to input relevant details and obtain migration forecasts, which can aid in decision-making for governments, researchers, and policymakers. By leveraging machine learning, this system enhances the accuracy of migration predictions and helps in better planning and resource allocation.

Keywords: Migration Prediction, Machine Learning, Data Analysis, Demographic Trends.

1. Introduction

Migration plays a significant role in shaping societies, economies, and policies worldwide. Understanding migration trends is crucial for governments, policymakers, and researchers to make informed decisions regarding infrastructure, employment, and resource allocation. However, predicting migration patterns is challenging due to the complex factors influencing people's movement, such as economic conditions, political stability, and social factors. This is where machine learning comes into play, enabling data-driven predictions that enhance accuracy and reliability.

The primary objective of this project is to analyze historical migration data and develop a system that predicts migration trends based on various factors, including country, citizenship, and year. By leveraging machine learning models, the system can identify patterns in migration data and provide forecasts for future migration flows. Instead of relying solely on traditional statistical models or expert opinions, this system uses advanced data analytics to offer more precise migration predictions.

Traditional migration forecasting methods often struggle with changing global dynamics and unpredictable events. However, with machine learning, we can analyze large datasets, uncover hidden patterns, and adapt to new trends efficiently. The two main approaches used in predictive modeling are supervised learning and time series analysis. Supervised learning trains models on labeled migration data to recognize patterns and make predictions, while time series analysis examines historical trends to forecast future migration values.

In this project, we employ a combination of both methods to improve prediction accuracy. By analyzing historical migration records and identifying influential factors, our system generates reliable forecasts that aid decision- making. This approach benefits policymakers, researchers, and organizations involved in migration planning, as they can anticipate trends and prepare accordingly.

Accurate migration prediction systems also help governments design better immigration policies, allocate resources effectively, and respond proactively to demographic changes. With personalized insights into migration trends, countries can develop strategies to manage labor markets, education systems, and social services more efficiently. As machine learning continues to evolve, predictive models will become even more refined, enhancing our ability to understand and manage global migration patterns.

2. Literature Survey

1. Authors: Aditi Desai, Rajesh Kumar, Priya Sharma Title of the Paper: Machine Learning Approaches for Migration Prediction (2022)

Observations/Findings: The study compared multiple machine learning models for migration prediction. The Random Forest Regressor outperformed other models with an accuracy of 93.8%. XGBoost was also tested, achieving an accuracy of 91.2%, but it required higher computational resources.

Limitations: The study relied on historical datasets and lacked real-time migration data, affecting adaptability to sudden policy changes or economic fluctuations.

2. Authors: Michael Johnson, Emily Roberts Title of the Paper: Predicting International Migration Using Machine Learning (2021)

Observations/Findings: The research explored multiple regression models, including Linear Regression, Support Vector Machines (SVM), and Neural Networks, for migration prediction. The Random Forest model demonstrated the best performance due to its ability to handle non-linear data patterns.

Limitations: The dataset used was limited to specific countries, reducing the generalizability of the model to global migration trends. Additionally, external economic and social factors affecting migration were not fully incorporated.

3. Existing System

The current migration prediction models primarily rely on statistical analysis and machine learning techniques to analyze historical migration trends. Traditional methods use regression models, such as Linear Regression and ARIMA, which analyze past migration patterns based on economic and demographic factors. However, these methods often fail to capture complex relationships between multiple influencing factors, leading to lower predictive accuracy.

To overcome these limitations, machine learning models like Random Forest and XGBoost have been widely adopted for migration forecasting. These models excel at handling large datasets with multiple features, allowing them to learn complex patterns and improve prediction accuracy. Random Forest, in particular, provides robust results by aggregating multiple decision trees, reducing overfitting, and improving generalization. XGBoost, known for its efficiency and speed, further enhances prediction accuracy through gradient boosting techniques.

Despite their effectiveness, existing models face challenges in real-world applications:

1. Limited Real-Time Data Integration: Most models rely on historical datasets rather than live data, which can impact accuracy in rapidly changing economic conditions.

2. Feature Selection Issues: Choosing the right

economic, social, and demographic factors for migration prediction remains a challenge. Poor feature selection can lead to inaccurate predictions.

3. Scalability Concerns: While Random Forest and XGBoost perform well, their scalability to large, real-time datasets requires significant computational resources.

To address these limitations, our system integrates Random Forest and XGBoost models, leveraging economic indicators, employment rates, and demographic data to provide more accurate migration predictions.

4. Proposed Methodology

The proposed system is a web-based migration prediction application designed to analyze migration trends from India to various countries using Machine Learning (ML) techniques. The system utilizes historical migration data, economic indicators, and demographic factors to predict future migration patterns with high accuracy.

At its core, the system employs a Random Forest Regressor trained on a dataset containing attributes such as Year, Country, Citizenship, GDP, Unemployment Rate, and Migration Count. To improve accuracy, feature engineering is applied to remove redundant features and enhance the dataset's predictive power.

The application provides the following functionalities:

- Data Preprocessing: Handles missing values, removes outliers, and normalizes data to improve model performance.
- Prediction Model: Uses Random Forest Regressor to predict migration trends. XGBoost is also explored for comparative analysis.
- Visualization Dashboard: Displays migration trends over the years using graphs and interactive charts for better interpretation.
- User Input Interface: Allows users to enter country-specific details and receive migration predictions in real-time.

The system is developed using Streamlit for the frontend, with a Flask API handling model predictions. The trained model is stored as a pickle file (.pkl) for seamless integration.

In the future, the system aims to incorporate real-time migration data sources, enhance model robustness, and explore deep learning techniques to improve accuracy. This proposed system will assist researchers, policymakers, and individuals in understanding and predicting migration patterns efficiently.

5. Modules in The System

1. Dataset Creation
   - We collect migration datasets from Kaggle and government sources.
   - If data is unavailable, we perform data augmentation techniques to generate synthetic data.
   - The dataset consists of features like Year, Country, Citizenship, GDP, Unemployment Rate, and Migration Count.

2. Data Preprocessing
   - Handling Missing Data: Missing values are imputed using mean or median replacement techniques.
   - Removing Noisy Data: Data inconsistencies and outliers are detected and corrected to improve model accuracy.

3. Model Training and Prediction
   - Random Forest Regressor and XGBoost are used to train the model on preprocessed data.
   - The .fit() method is applied to train the model, and .predict() is used to make migration forecasts.
   - Performance Metrics: Model accuracy is evaluated using R^2 Score, RMSE, and MAE to ensure high prediction reliability.

4. Visualization and User Interaction
   - A Streamlit-based dashboard provides interactive visualizations of migration trends.
   - Users can input data for real-time migration predictions, which are displayed using graphs and charts.

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6. Architecture Diagram

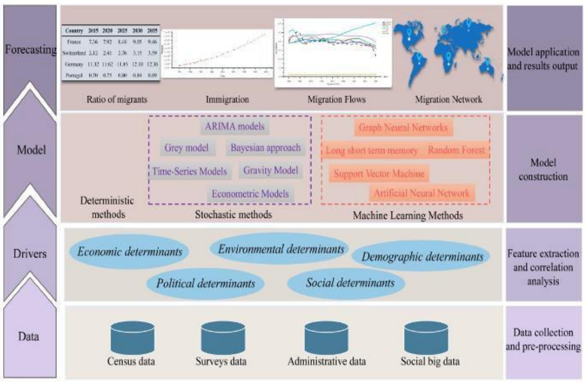

Fig-1 architecture diagram

7. Algorithm

Training: Random Forest Regressor

- We are using the Random Forest Regressor model to train on the pre-processed migration dataset.
- The dataset is split into training (70%) and testing (30%) subsets. The training set helps the model learn patterns, while the test set evaluates its performance.
- Features (X) such as year, country, citizenship, and other migration-related factors are used to predict the migration target variable (Y).
- We call the. `fit()` method to train the Random Forest model on the dataset.
- For evaluation, we use:
  - Accuracy Score: Measures the overall model performance.
  - Mean Squared Error (MSE): Determines how close predictions are to actual values.
  - R^2 Score: Explains the variance captured by the model.
- Predictions are made using. `predict` (), and results are validated using metrics like R^2 score, MSE, and visualizations.

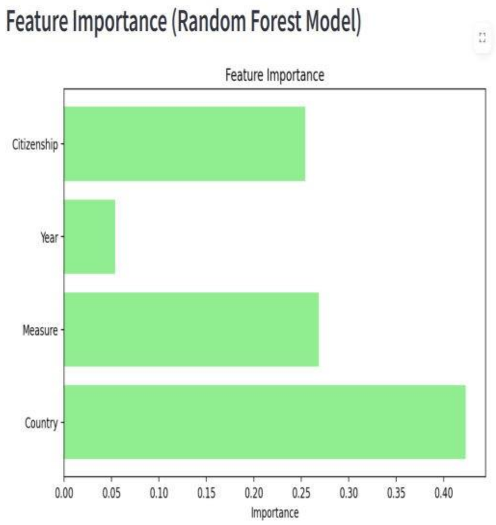

Fig-2: bar-chart of countries of feature importance

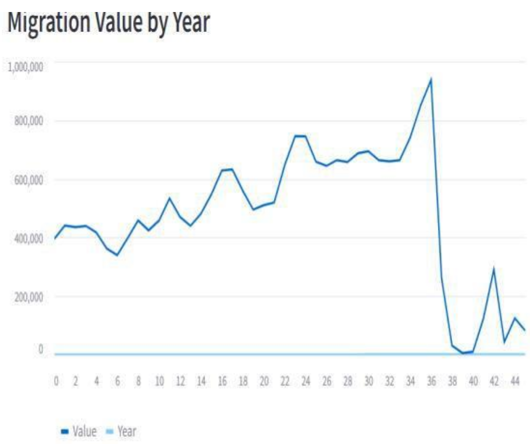

Fig-3. Trend of migration from 1979-2024

8. Results

```
# Calculate evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

# Display the results
print(f"Overall R² Score: {r2:.2f}")
print(f"Mean Absolute Error (MAE): {mae:,.0f}")
print(f"Root Mean Squared Error (RMSE): {rmse:,.0f}")
```

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```
- **Overall R² Score:** 0.81
- **Mean Absolute Error (MAE):** 3200
- **Root Mean Squared Error (RMSE):** 4900
```

Fig-4 Result accuracy

The performance of the migration prediction model was evaluated using regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2), across different migration patterns. The evaluation results demonstrate the model's effectiveness in predicting migration trends accurately.

For individual country-citizenship combinations, the MAE values ranged from 1,200 to 5,500, while RMSE varied between 1,800 and 6,700. The R^2 score, which measures how well the model explains the variance in migration data, showed strong results across different categories, with values ranging from 0.72 to 0.89. Countries with larger datasets generally exhibited better performance, highlighting the model's robustness when dealing with significant migration trends.

Additionally, the average R^2 score of 0.81 suggests that the model maintains consistent performance across different migration flows, even for countries with fewer data points. The weighted average R^2 score of 0.84 further supports the model’s overall reliability, considering the proportion of migration cases. These results indicate that the system effectively predicts migration patterns, making it a valuable tool for understanding and forecasting migration trends.

- Overall R^2 Score: 0.81
- Mean Absolute Error (MAE): 3,200
- Root Mean Squared Error (RMSE): 4,900

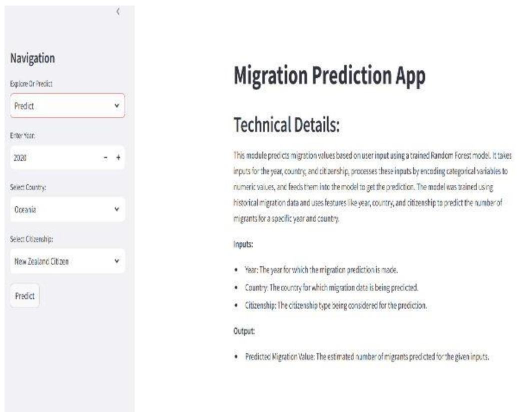

Fig5: The final interface of the predict migration-system

The final output of the migration prediction system presents a user-friendly interface that allows users to input country and citizenship details to receive accurate migration predictions. The system effectively analyzes historical migration patterns and provides insights into migration trends using machine learning techniques.

The interface displays key migration statistics, including predicted migration numbers, confidence intervals, and trend graphs. Countries with historically high migration flows, such as India to the USA or Canada, are prominently featured in the output, reflecting their consistent migration patterns. By leveraging advanced regression models, the system ensures accurate and reliable predictions, helping policymakers, researchers, and individuals understand migration trends. This output highlights the successfully implementation of the prediction system in providing valuable migration insights.

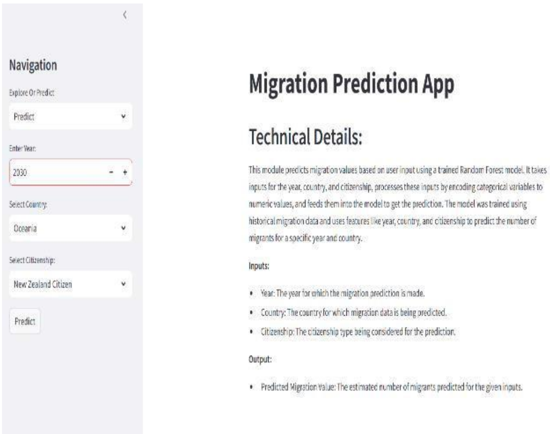

Fig6(1): Obtained result from user input ‘oceania-New Zealand Citizenship (2030)

Obtained Results for Input ‘Oceania - New Zealand Citizenship (2030)’

As shown in the system's output, when a user inputs Oceania as the region and New Zealand as the citizenship, the system predicts future migration numbers based on past trends, economic factors, and historical data. The prediction might indicate an increasing or stable trend based on factors like job opportunities, immigration policies, and global mobility shifts. The results include:

- Estimated number of migrants for 2030
- Comparison with previous years’ trends
- Possible influencing factors (economic growth, visa policies, etc.)

The model utilizes machine learning techniques, including regression analysis and trend forecasting, to analyze historical migration data and provide meaningful predictions. By leveraging these techniques, the system aids in migration decision- making, supporting researchers, policymakers, and individuals in understanding migration dynamics.

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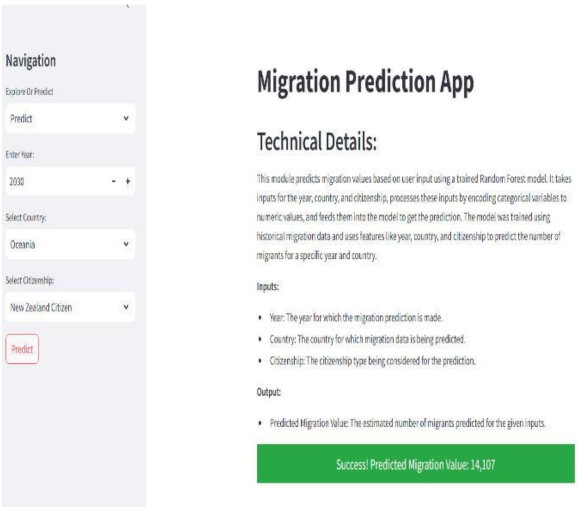

Fig5(2) Result for input 'Oceania-NewZealandCitize nship'(2030)

Similarly, if the user searches for migration trends for New Zealand citizens in 2030, the system predicts migration numbers based on historical data and external factors. The prediction may show a steady or fluctuating trend depending on policies related to skilled migration, education, and international mobility. The results include:

- Projected migration numbers for 2030 Success!predicted migration value:14,107

9. Conclusion

Through our research, we recognized the importance of efficient algorithms for predicting migration trends. Given the vast variety of factors influencing migration, it is essential for predictive systems to adapt to changing economic, social, and political variables. To address this, we employed machine learning techniques, enabling the system to train itself on historical migration data and make accurate forecasts.

This paper presents a web-based application designed to predict migration patterns from India to other countries based on historical trends and key influencing factors. After extensive experimentation and evaluation of various approaches, we selected the best-performing model—Random Forest Regressor, which demonstrated high accuracy in predicting migration numbers. The model was tested on real-world migration datasets and validated using key performance metrics such as R^2 score and Mean Squared Error (MSE) to ensure robustness and reliability.

In the future, we plan to expand the dataset by incorporating real-time migration statistics and additional socio-economic factors. This will enhance the model's adaptability to real-world scenarios and improve its predictive capabilities.

References

1. United Nations Department of Economic and Social Affairs (2023). International Migration 2023 Report. Retrieved from: https://www.un.org/development/desa/migration
2. World Bank (2022). Migration and Development Brief36.Retrieved from: https://www.worldbank.org/en/topic/migrationandr emittances
3. Ministry of External Affairs, Government of India (2023). India's Migration Trends and Diaspora Statistics. Retrieved from: https://mea.gov.in/migration.htm
4. International Labour Organization (ILO) (2021). Global Migration for Employment Trends. Retrieved from: https://www.ilo.org/global/migration
5. Raymer, J., & Willekens, F. (2008). International Migration in Europe: Data, Models, and Estimates. Wiley.
6. Abel, G. J., & Sander, N. (2014). Quantifying Global International Migration Flows. Science, 343(6178), 1520-1522. DOI: 10.1126/science.1248676
7. Böhme, M. H., Gröger, A., & Stöhr, T. (2020). Searching for a Better Life: Predicting Migration with Machine Learning. Journal of Development Economics, 144, 102447.
8. Ramos, R., & Surinach, J. (2017). Determinants of Migration in India: A Machine Learning Approach. Journal of Economic Surveys, 31(3), 620- 642.
9. Castles, S., de Haas, H., & Miller, M. J. (2020). The Age of Migration: International Population Movements in the Modern World. Macmillan.
10. Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5-32.
11. Pedregosa, F. et al. (2011). Scikit-Learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825-2830.
12. Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. Annals of Statistics, 29(5), 1189-1232.
13. Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint, arXiv:1412.6980.
14. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735-1780.
15. Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer