Human Migration Predictor

PROJECT SYNOPSIS (14pt. bold)

<u>Machine Intelligence</u>

BACHELOR OF TECHNOLOGY- V Sem CSE

Department of Computer Science & Engineering

SUBMITTED BY

Batch No: -

Student name 1:Thushar M	SRN:PES1UG20CS471
Student name 2:Varun S R	SRN:PES1UG20CS491
Student name 3:Tejas Goyal	SRN:PES1UG20CS466

PES UNIVERSITY

(Established under Karnataka Act No. 16 of 2013)

100 Feet Ring Road, BSK III Stage, Bengaluru-560085

Abstract and Scope :

Human migration can be defined as the movement of people from one place to another place with the intention of settling, either permanently or temporarily, at a new location. People may migrate as individuals, in family units or in large groups. The movement often occurs over long distances and from one country to another country. According to the World Economic Forum, there are an estimated 272 million international migrants around the world. And while that equals just 3.5% of the world's population, it already surpasses some projections for 2050. Since 1970, the number of people living in a country other than where they were born has tripled.

Reasons for Migration:-

1. Economic Migration — moving to find work or follow a particular career path.
2. Social Migration — moving somewhere for a better quality of life or to be closer to family or friends.
3. Political migration — moving to escape political persecution or war.
4. Environmental causes of migration include natural disasters such as fires and flooding.

Traditional human mobility models, such as gravity models or the more recent radiation model, predict human mobility flows based on population and distance features only. These models have been validated on commuting flows, a different type of human mobility, and are mainly used in modeling scenarios where large amounts of prior ground truth mobility data are not available. One downside of these models is that they have a fixed form and are therefore not able to capture more complicated migration dynamics. We propose machine learning models that are able to incorporate any number of exogenous features, to predict origin/destination human migration flows. Our machine learning models outperform traditional human mobility models on a variety of evaluation metrics. Predicting human migration as accurately as possible is important in city planning applications, international trade, spread of infectious diseases, conservation planning, and public policy development. There are three main approaches that provide informed guesses about future migration trends. These include the following:

1. Early Warnings System: Uses quantitative and qualitative data to monitor potential drivers and movements of populations in real time to provide short-term estimations in fast-changing contexts. These systems establish

pre-defined warning thresholds, that when exceeded, trigger specific actions to be taken by designated individuals.

2. Forecasting: Predicts future migration flows and trends using quantitative modelling methods with a medium and long-term horizon. This approach statistically models future migration trends based on quantitative data from the past. This type of modeling needs a significant amount of numerical data related to migration such as policy changes and past inflows and outflows of migrants by location.
3. Foresight: Uses qualitative scenario methods like "What if… to describe future migration flows and trends. Migration scenarios are qualitative narratives about the future of migration that examine possible structural changes and their consequences for migration

Feasibility Study:

Modeling human migration and population dynamics is vital for governments and social scientists so that they may effectively prepare jobs and living spaces for influxes of people fleeing war, famine, climate change, or discrimination, along with those simply seeking a better economic standing. One downside of traditional models is that they have a fixed form and are therefore not able to capture more complicated migration dynamics. International migration flows are volatile and difficult to anticipate but some types of movements are more stable or more regulated than others, hence more predictable. The most difficult part of migration flows to anticipate is certainly related to forced and irregular movement. This is, however, where there is the greatest need for contingency planning and/or to quickly adapt asylum and reception services. Labour and family migration, including within free mobility areas, are theoretically easier to foresee, although it requires a sharp understanding of push and pull factors as well as of individual behaviour. Anticipating these flows is particularly useful to support integration service providers at national and local levels.

Design Approach/ Methodology/ Planning of work :

The following steps will be performed using machine learning and Python.

1. Import the required software libraries.

2. Access and import the dataset.

3. Data Analysis and Exploration.

4. Split the data into test and training data sets.

5. Train the model on the training data.

6. Make predictions on the test data.

7. Evaluate the model's performance.

8. Optimize to further improve accuracy.

9. Draw conclusions from evaluations.

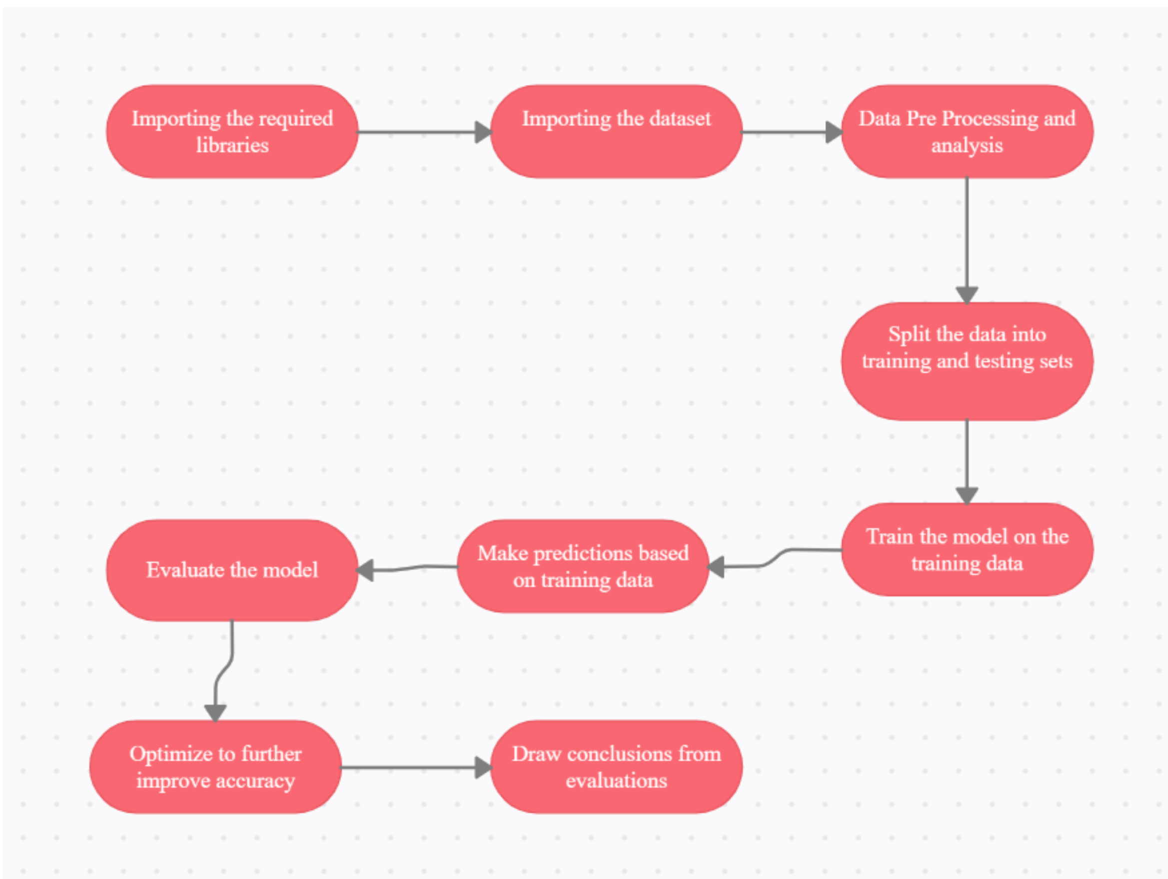
We obtained the migration dataset from Github. This dataset includes the following variables:

1. Measure — The signal type given in this row including "Arrivals", "Departures", "Net".
2. Country — Country from where people arrived into New Zealand (for Measure = "Arrivals") or to where they left (for Measure = "Departures"). Contains special values "Not Stated" and "All countries" (grand total).
3. Citizenship — Citizenship of the migrants including "New Zealand Citizen", "Australian Citizen", "Total All Citizenships".
4. Year — Year of the measurement (arrival or departure).
5. Value — Number of migrants.

Dataset Link:- https://github.com/amankharwal/Website-data/blob/master/migration_nz.csv

The algorithm to be used is a random forest regressor. A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting

Architectural Diagram:



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