AVE **Trends in Intelligent Computing Systems**

Machine Learning-Based Population Forecasting Model with Power BI Visualisation for Decision Support

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Abstract: Today's populations are increasing, which is unpredictable for a common individual. Also, it becomes harder for him to construct the correct volume needed for the upcoming year. This can be solved by providing a future population-finding model. Neighbourhood and state legislatures rely on limited regional population figures to make significant decisions about the development of local infrastructure and services, including education, transportation, healthcare, energy, telecommunications, and water supply. Despite their significance, current techniques often yield highly inaccurate results, particularly at the small scale. Over the years, there have been promising improvements in time-series forecasting using Artificial Intelligence across many social and economic factors. In the proposed work, Machine Learning helps us solve many problems, including predicting future population growth. The objective of this paper is to analyse the specific prediction area and determine the need for prediction. Then, gather the best dataset for that specific area of a specific need to be predicted. With the help of a Machine Learning algorithm, the issue can be solved more precisely. Then, select a suitable Machine Learning model for our dataset. Power BI is used to create an interactive dashboard for users that provides a better understanding of the prediction output data. By properly implementing the methodology, the user will be able to determine the construction or business volume to enter.

Keywords: Machine Learning; Dynamic Dashboard; Artificial Intelligence; Linear Regression; Random Forest; Support Vector Machines; Decision Trees; Artificial Neural Networks.

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1. Introduction

One of the biggest problems facing the world in the twenty-first century is population increase. It affects almost every area of social, economic, and environmental development. An average person can't forecast how the population will change because it is affected by many interconnected factors, such as migration, birth and death rates, urbanisation, economic growth, and policy changes. Because of this uncertainty, it is becoming harder for people, corporations, and governments to plan for their future needs. People and policymakers sometimes don't know what to do when it comes to planning construction, building infrastructure, or figuring out how many resources and services will be needed in the future. Models that can accurately forecast future population can help solve these problems by enabling data-driven decision-making. Population forecasting is important across many areas, including healthcare, urban planning, transportation, education, water supply, energy distribution, and telecommunications. State and regional governments use population estimates to plan and run local services and infrastructure. For instance, educational authorities need to know how many school-aged children there will be so they can ensure there are enough classrooms and teachers [6]; [8]. Transportation departments use demographic predictions to plan public transit systems and road networks. Healthcare planners also need population projections to make sure that hospitals, clinics, and emergency services are in the right places. In short, accurately anticipating the population is the basis for strategic planning and good government.

Even though it's important, many current approaches for predicting population growth yield highly inaccurate or inconsistent results, especially at the community or regional levels. Conventional statistical methods often rely on limited historical data and linear assumptions that do not adequately capture the nonlinear and dynamic trends in population fluctuations. Because of this, traditional models may not fully account for new patterns such as rapid migrant surges, policy changes, economic crises, pandemics, or environmental changes. Furthermore, the intricacy of population behaviour complicates the formulation of a singular model that functions uniformly across all geographic regions and demographic settings. This restriction has led researchers and practitioners to investigate more sophisticated, data-driven methodologies for population forecasting. Artificial Intelligence (AI) and Machine Learning (ML) have become very useful technologies for solving difficult predictive problems in several areas over the last few years. These technologies have shown great promise in predictive analytics, time-series forecasting, and decision-support systems. Machine learning algorithms can find complex associations between variables that standard statistical models sometimes miss by learning patterns from historical and contextual data. As a result, AI-based forecasting systems are increasingly used across areas such as banking, climate prediction, sales forecasting, and energy consumption estimation.

Applying this method to predicting population growth could be a good way to make demographic forecasts more accurate and trustworthy. The proposed project focuses on utilising Machine Learning techniques to forecast future population growth in certain regions. The goal is to create a smart system that can analyse regional demographic data, identify patterns, and make accurate predictions for the next few years. This study focuses on selecting and assessing eligible datasets and identifying the most suitable machine learning algorithm to achieve optimal predictive accuracy. Using modern computer models, it is feasible to identify hidden connections among many factors that affect population dynamics, such as birth and death rates, migratory flows, and socioeconomic indices [7]. You can use many techniques to build machine learning-based population prediction models. These include Linear Regression, Random Forests, Support Vector Machines (SVMs), Decision Trees, and Artificial Neural Networks (ANNs). Depending on the type of data and the size of the prediction, each algorithm has its own pros and cons. For example, regression-based models might work well for steady population growth patterns, whereas ensemble or neural network-based models can handle more complex, nonlinear interactions. Choosing the optimal model depends on factors such as how easy it is to obtain data, how fast it runs, how easy it is to understand, and how accurate it is at predicting.

This study compares and improves multiple models to get the most accurate forecasting outcomes. Data collection and preparation are two of the most important parts of this work. The quality of input data is very important for accurate population forecasting. Datasets must contain variables that directly or indirectly affect population growth. These could include demographic information, census data, birth and death statistics, migration rates, literacy levels, employment statistics, and other socioeconomic indicators. In some circumstances, satellite or geospatial data can help improve prediction accuracy by providing information on population density and land use across different areas. It is important to clean, normalise, and preprocess this data before putting it into a machine learning model. This will remove any inconsistencies or outliers that could impair the model's learning. After training and testing the model, the findings need to be shown to users in a way that they can understand and use. Power BI and other visualisation tools make it easy to display massive, complex datasets interactively. Power BI lets customers see predictions, trends, and analytical insights through dashboards and interactive visualisations. Power BI is the user interface that shows the results of the population prediction made by the machine learning model in this suggested study.

This integration helps planners, decision-makers, and even people understand demographic trends and make smart choices about future construction, infrastructure expansion, or corporate investments. So, Machine Learning and Power BI together make a complete system for predicting and showing population data. Machine Learning does the analytical work, finding patterns and making predictions. Power BI then turns these results into a clear, interactive visualisation. This integration makes it easier for everyone to understand data by turning technical model outputs into insights that non-technical people can easily understand. This method not only makes things easier to access but also makes the prediction outcomes clearer and more trustworthy. From a broader perspective, accurate population forecasting supports sustainable development goals and smart resource management. Governments and city planners can utilise predictive analytics to plan cities that accommodate more people while still maintaining environmental balance. For example, knowing how a city's population can change helps the government get ready for housing demand, waste management, water supply, and energy needs. In the same way, firms in the private sector can utilise population estimates to determine the size of the market and the number of customers they will have in the future. Construction companies, for instance, can determine how many supplies, workers, and dollars they will need based on how many people are expected to move to certain areas.

The United Nations (UN) and the World Bank are two organisations that emphasise the importance of accurate demographic data for long-term planning and policy-making at the global level. The UN's most recent estimates say the world's population will reach around 10 billion by 2050, with most of the growth occurring in poorer countries. Policymakers face both opportunities and challenges due to rapid urbanisation and population changes. Machine learning-based population prediction models can help us prepare for these changes at the local and national levels, enabling us to respond quickly and effectively. The uncertainty of human movement underscores the necessity for sophisticated modelling methodologies. Conventional population forecasting models frequently neglect to account for short-term migratory trends driven by political instability, economic prospects, or environmental calamities. Machine learning models, on the other hand, may update their predictions based on new data, allowing them to keep improving. This ability to adjust in real time ensures that forecasts remain useful and accurate, even when conditions change. Machine learning models can also combine data from many sources, such as census reports, satellite images, internet polls, and free government databases, to provide a more complete picture of how populations change. Using big data and AI, we can make highly accurate predictions that reveal subtle patterns within cities or districts rather than relying on large-scale national projections.

These granular insights are very useful for running cities, as decisions are typically made at the local level. Another important part of the proposed study is checking how accurate the predictions are. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared values are some of the most used ways to evaluate machine learning models. These numbers show how well the anticipated values match the real historical data. The research identifies the best algorithm for predicting population by evaluating different models and performance indicators. To ensure a model is strong and performs well across diverse datasets and time frames, it needs to be continuously tuned and validated. Power BI connection also makes it easier to understand these results. Visual dashboards can show how the population will change in the future, by location, age group, or gender. This gives you a better idea of how demographic structures work. With interactive charts, viewers can explore "what-if" scenarios, including how varying birth or migration rates might change the population's size in the future. This feature turns the model into more than just a way to make predictions; it also helps policymakers and planners look at different options and make decisions. Putting such a framework in place makes a big difference in making decisions based on facts. Stakeholders can utilise data-driven forecasts to inform investment and policy decisions, rather than relying on gut feelings or outdated estimates. For instance, if a city's population is expected to increase significantly over the next 10 years, local governments can get ahead of the curve by expanding housing programs, transit systems, and schools. On the other hand, areas with shrinking populations can grow by reallocating resources or enacting laws that encourage people to move there and boost economic activity.

This research not only has practical applications but also contributes to the academic field by demonstrating how machine learning can be effectively applied to demographic studies. The work connects data science with population analysis by showing that AI-driven methods can be more accurate and flexible than traditional demographic models. This framework advances the idea of intelligent decision-support systems for urban and regional planning by combining machine learning algorithms with visualisation tools such as Power BI. The ultimate objective of this research is to enable users—whether individual builders, municipal authorities, or corporate proprietors—to make more informed decisions about future growth. Users can determine how large construction projects should be, how much businesses should invest, and how many resources should be allocated by knowing how many people are expected to live in a given area. In short, the method turns complex demographic predictions into a useful tool that helps society grow and plan the economy. Combining Machine Learning and Power BI to anticipate population growth is a smart, modern way to address one of the oldest problems people have faced: predicting population changes. It combines the analytical power of AI with the communicative power of visualisation to make a solution that is easy to use and scientifically sound. Better planning, more efficient resource use, and long-term growth in cities can result from accurate, easy-to-understand population forecasts. As populations keep growing in unexpected ways, these new methods are no longer optional; they are necessary for being ready for the future with confidence and accuracy.

2. Review of Literature

Small-area population estimates are widely used by government and business for various reasons. They illuminate choices about the development and allotment of funding for streets, schools, aged care services, transport, and wellbeing services, among other purposes [1]. However, small-region population estimates are more likely to err than gauges at larger geographies. The more modest the populace, the bigger the mistake will generally be, especially for populations of only a couple of thousand individuals [2]. To some degree, this is because information sets for small regions often have short time series, less precise data, data quality issues, and noisy examples [3]. In any case, it is also due to the limited amount of research devoted to estimating small-area populations compared to public-level gauging. Lately, one of the key areas for advances in time series estimation has been Machine Learning (ML). Notwithstanding, writing research on the turn of events and the assessment of these techniques on small regional population datasets remains limited [4]. We use Kera's Tuner to select layer unit numbers, adjust the window width of the information, and apply a twofold preparation and approval system that supports work with short-term time series and focuses on later grouping values for estimates. These strategies are adaptable and can be applied to different informational collections. A review of population Figures for the little region of Australia was conducted for the periods 2006-16 and 2011-16. Model execution was compared with genuine data and two benchmark strategies. The profound learning techniques delivered estimates similar to the benchmark techniques, particularly for the 2006-based conjectures, but not for the 2011-based Figures generated by one of the benchmark techniques. Nowadays, we can't predict the future population for our Business, road and building construction to be carried out in accordance with the required measures.

The amount of croup cultivation is to be known. To increase the country's economic structure [5]. Prof Stein Emil Vollset, DrPH, has discussed possible future population levels as a basis for anticipating and planning for changing age structures, resource and healthcare needs, and ecological and economic contexts. Future richness designs are a vital contribution to assessing future population size; however, they are encircled by significant uncertainty and differing assessment and determination procedures, leading to substantial differences in global population projections. Changes in population size and ageing demographics can have significant financial, social, and international effects across many nations. Tom Wilson, Irina Grossman, Monica Alexander, Phil Rees and Jeromey Temple have discussed that little-region population estimates are generally used by government and business for different planning, research, and strategy purposes, and that they frequently influence significant investment decisions. In any case, the tool stash for small-region population estimation strategies and procedures is modest compared to those for public and large subnational provincial estimation. In this paper, we survey the current state of population expectations in small regions and recommend areas for further research. The paper provides an overview of the literature on population estimation techniques in small regions published between 2001 and 2020. The primary objective of this paper is to improve the overall efficiency of population forecasting by building long-term structures, creating a user-friendly Prospect model, developing an accurate Machine Learning Model, building a back-end server with Flask, and designing a good-looking UI with Angular.

3. Methodology Block Diagram

The proposed Block diagram shown in Figure 1 shows the flow of Data from the User to the ML model and back to the frontend for result display. Over the years, there have been promising improvements in time-series forecasting using AI across many social and economic factors. In general, no research has been undertaken on their likely application in demography, especially for small-area population estimation. In this paper, we present improvements to two Long-Transient Memory network models for working with small region populations:

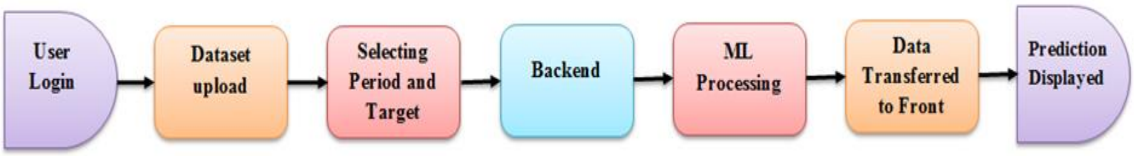

Figure 1: Block diagram

- **Login Page:** The user must log in to the website using the credentials from their sign-up. This login page is created with Angular CLI. On the login page, when a user tries to log in, it verifies the credentials against existing data. It is connected to MongoDB via a Flask backend server. After verification, it directs to the Data input page. When a new user enters data in the signup tab, it will be sent to the backend server. Now that this user has been added to the database, he can access the web app whenever needed.
- **User Input:** After user login, on this page, the user has to upload their dataset for a specific area. Then he has to click on the upload button. At that time, the dataset will be uploaded into the database. Then he has to select a period, e.g., daily, weekly, monthly, quarterly, or yearly. After selecting the period, he must select the target, i.e., the number of days of data to be predicted. Finally, the summit button is clicked, and the prediction process is initiated in the backend.
- **REST API Call:** To send GET requests with query URL strings and parameters and process HTTP responses from REST API servers in your Angular 12 application using HttpClient to retrieve and consume JSON data, how to perform error handling for HTTP errors using RxJS throwError() and catchError() operators, how to retry failed HTTP requests on bad network connections and cancel outstanding requests using RxJS retry() and takeUntil() operators [9].

- **Flask Server:** Flask is a Python web framework. It is developed by Armin Ronacher, who leads an international group of Python enthusiasts called Pocco. Flask is built on the Werkzeug WSGI toolkit and Jinja2 templates. Both are Pocco projects [10].
- **Data Displayed:** After all preprocessing, the training and prediction data are then transferred to the frontend and displayed in chart format for better understanding. For the chart, the Chart.js library is used to improve understanding.

4. Prophet Model

4.1. Population Data

We got population statistics for the longest time series that used the same set of geographical borders for statistical area level 2 (SA2) areas. These are the smallest official spatial units for which estimated population figures (ERPs) have been released. The data is made up of yearly ERP totals from 1991 to 2016, depending on the geography of 2011. In 2016, the average population of a SA2 in Australia was 9,681. 95% of SA2s had populations between 2,559 and 29,279. We didn't train the model on SA2 regions where the population was less than 100 during any of the year's assembly periods. These groups were put together into a "residual" region that was not used for training but was used for forecasts. This way, the forecasts could be limited to a nationwide forecast. National population projections were needed as data inputs or limits for small area forecasts. We chose the ABS's main series estimates that were closest to the leap-year forecasts for 2006 and 2011.

4.2. Data Pre-Processing

Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data preprocessing is the process of converting raw data into a clean dataset. In other words, when data is collected from various sources, it is in a raw format that is not suitable for analysis [11]; [12].

4.3. The Need for Data Pre-Processing

To get better results from the model used in machine learning projects, the data format must be correct. Some machine learning models require data in a specific format; for example, the Random Forest algorithm does not support nulls, so to run it, nulls must be handled in the original raw data set. Another aspect is that the dataset should be formatted to run multiple machine learning and deep learning algorithms on a single dataset and select the best one.

4.4. Time Series Forecasting

Statistical and modelling tools are used to look at time series data and generate predictions about the future. This is called time series forecasting. This isn't always a good prediction, and the chances of a prediction can be very different, especially when working with time-series data that often changes and with things we can't control. Predictive insight on which outcomes are more likely or less likely than other possible outcomes. In many cases, the more complicated the data we have, the more accurate the predictions can be. prediction and "forecast" usually mean the same thing, however there is a big difference. In some fields, "forecasting" means data from a certain point in the future, whereas "prediction" means data from the future in general. Time series analysis and series forecasting are commonly used together. To learn more about the data and find out what caused it, time series analysis requires developing models. Analytics can tell you why you get the results you get. Then, forecasting is the next step in using that information and generating educated guesses about what might happen in the future.

4.5. When Time Series Forecasting Should be Used

There are limits, of course, when dealing with things that are unforeseen or unknown. Time series forecasting isn't always right and isn't the best or most beneficial method for every case. There aren't clear rules on when you should or shouldn't utilise forecasting. Analysts and data teams need to recognise the limits of their analysis and what their models can handle. Not every model will work with every data set or give you the answer you need. When data teams know what a business question is and have the right data and forecasting skills to address it, they should use time-series forecasting. A smart forecaster can find true trends and patterns in past data and works with clean, time-stamped data. Analysts can tell the difference between random changes and outliers, as well as between true insights and seasonal changes. Time series analysis shows how data change over time, and a good forecast can indicate the direction of change [13]; [14].

4.6. New in Prophet

We want to be able to change the method's parameters to fit the specific scenario when the forecasting model isn't working as expected. To get these methods to perform better, you need to know a lot about how the time series models work. The maximum orders of differentiation, the number of autoregressive components, and the number of moving-average components are all examples of the first input parameters for automated ARIMA. Most analysts won't know how to change these commands to stop the activity, and that's the kind of knowledge that is hard to get and grow. The Prophet package has simple parameters that are easy to adjust. Even someone who doesn't know much about forecasting can use it to make useful predictions about different business issues.

4.7. Prophet Forecasting Model

We use a decomposable time-series model with three main components: trend, seasonality, and holidays. They are combined in Equation (1):

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \qquad (1)$$

Where:

- **g(t):** piecewise linear or logistic growth curve for modelling non-periodic changes in time series.
- **s(t):** periodic changes (e.g. weekly/annual seasonality).
- **h(t):** effects of holidays (provided by the user) with irregular timetables.
- **εt:** the error term accounts for all unusual changes the model did not capture.

Using time as a regressor, Prophet attempts to fit several linear and non-linear functions of time as components. Modelling seasonality as an additive component is the same approach as in the Holt-Winters technique, which uses exponential smoothing.

4.8. Trend

A trend is modelled by fitting a piecewise linear curve over the trend or non-periodic part of the time series. A linear fit exercise ensures that it is least affected by spikes/missing data.

4.9. Nourishing Growth

An important question to ask here is: Do we expect the target to rise/fall throughout the forecast interval? More often, there are cases of non-linear growth at maximum capacity. Let us see an example below.

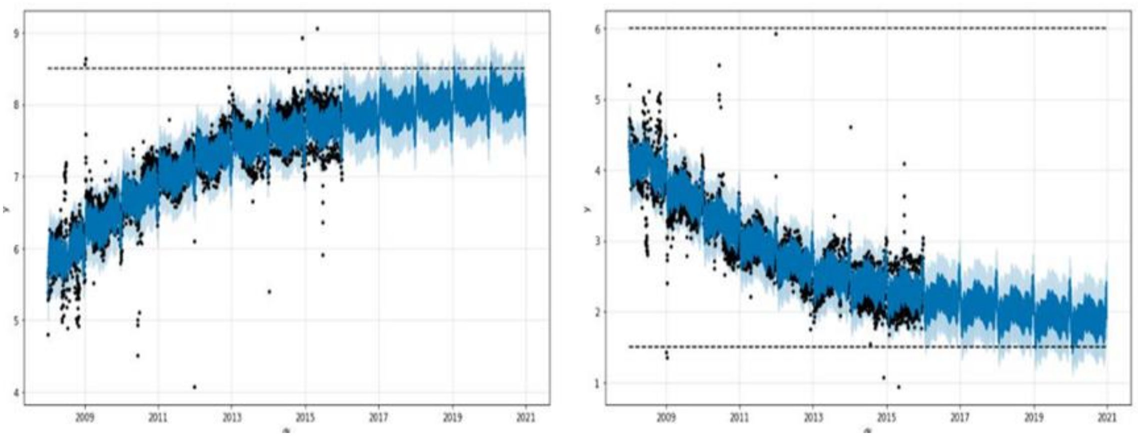

Figure 2: Projected upward growth trend

Figure 2 shows the nourishing growth. Let's say we're trying to predict the number of app downloads in a region for the next 12 months. The maximum number of downloads is always limited by the total number of smartphone users in the region. However, the number of smartphone users will increase over time. With the domain knowledge at his disposal, the analyst can define the variable capacity C(t) for the time series forecasts he is trying to make.

4.10. Points of Change

Another question to answer is whether my time series is experiencing any major changes, e.g., a new product launch, an unforeseen calamity, etc. At such points, the growth rate may change. These change points are selected automatically. However, the user can also enter change points manually if needed. In the graph below, the dotted lines represent the change points for that time series (Figure 3).

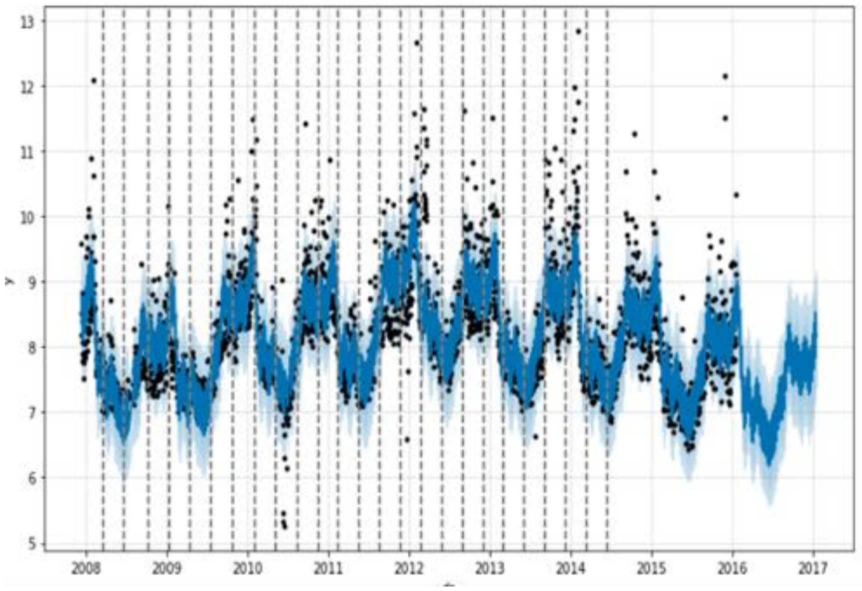

Figure 3: Points of change

As the number of allowed change points increases, customisation becomes more flexible. Basically, there are two problems that an analyst can face when working with the trend component: Overgrazing and Under-equipped. A parameter called the changepoint prior scale can be used to adjust the trend's flexibility and address the two problems above. A higher value will fit a more flexible curve to the time series.

4.11. Seasonality

To account for and predict seasonality, Prophet uses a Fourier series to provide a flexible model. Seasonal effects s(t) are approximated by the following function (2):

$$s(t) = \sum_{n=1}^{N}(a_n\cos(2\pi nt/P) + b_n\sin(2\pi nt/P)) \quad (2)$$

Where P is the period (365.25 for yearly dates and 7 for weekly dates). The parameters [a1, b1,…, aN, bN] need to be estimated for a given N to model seasonality. Setting the Fourier order N is crucial since it tells you if you can model changes that happen at high frequencies. If the user thinks that the high-frequency parts of a time series are just noise and shouldn't be used for modelling, they can set the Nod values to lower values. If not, you can change N to a larger amount and use the prediction accuracy to set it.

4.12. Holidays and Events

Holidays and events cause the time series to change in ways that can be predicted. For instance, Diwali is celebrated on a different day each year in India, and a lot of people buy a lot of new stuff around this time. Prophet lets the analyst build a list of events that have already happened and will happen in the future. The window surrounding these days is looked at independently, and other factors are changed to show how holidays and events affect everything.

5. Result and Discussion

5.1. Frontend Design

Users can get to the prediction web app via the login and signup pages shown in Figures 4 and 5. The user needs to make an account on the signup page if they are new. The data will be transferred to the backend and stored in the MongoDB database server after the researchers fill out their information. After all of these steps, he will be sent to the site where he can enter data. Figure 6 illustrates the screen where the user needs to upload the population dataset to the server.

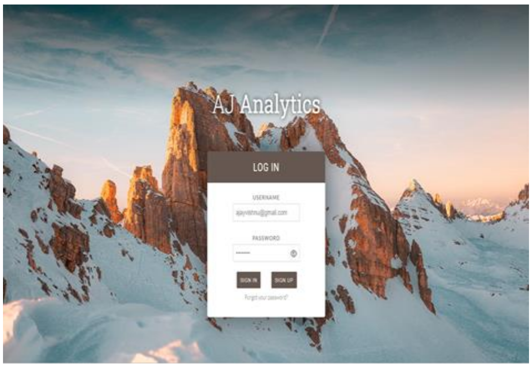

Figure 4: Login page

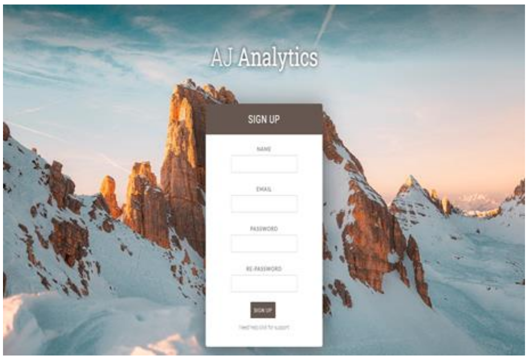

Figure 5: Signup page

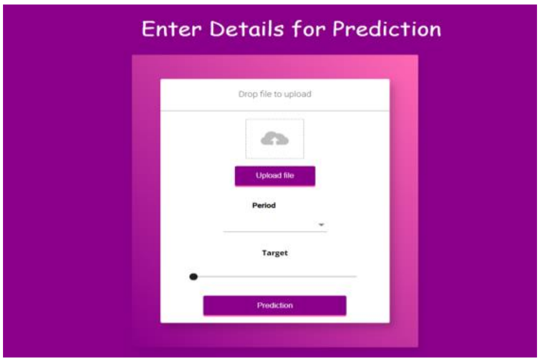

Figure 6: User data entry page

After data entry is complete, the prediction process will run on the backend server.

5.2. Output Chart

Figure 7 shows the final prediction output from our ML model, displayed as a line chart for better understanding.

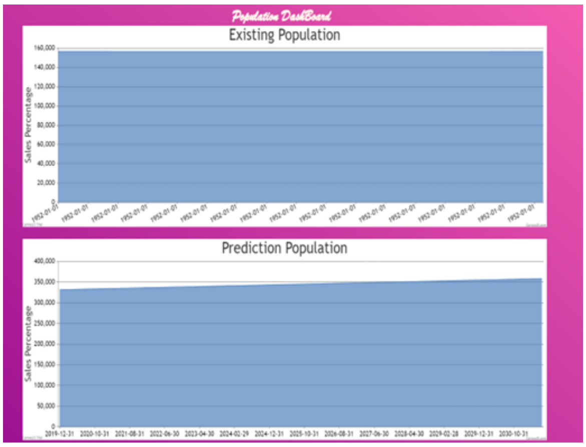

Figure 7: Result output page

5.3. Power BI

Figures 8, 9 and 10 show the Power BI dashboard for our predicted and pre-processed datasets. Power BI is a powerful tool for creating dashboards like this; it makes the data more interactive and provides a better understanding of the data than before.

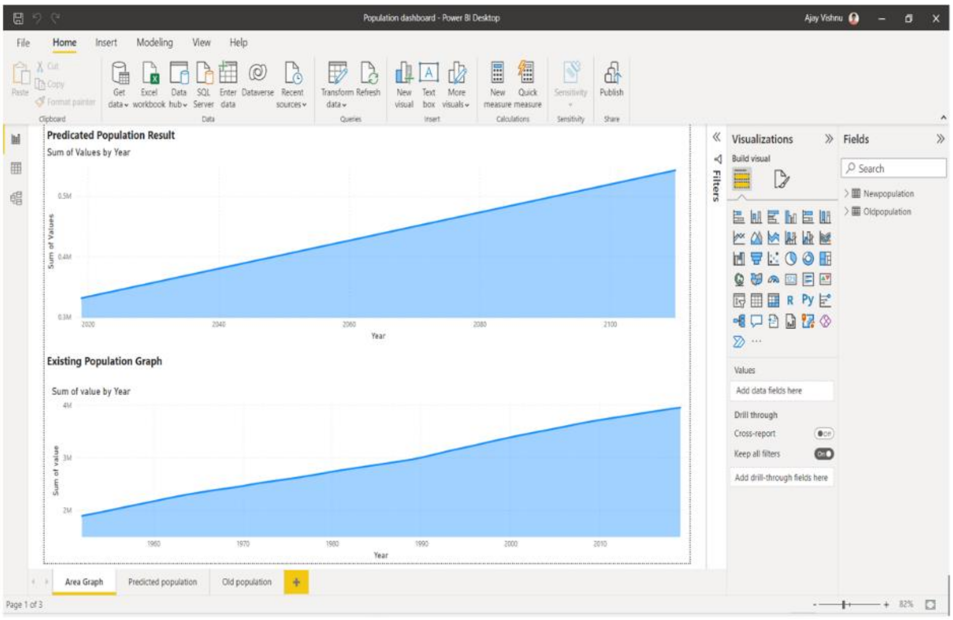

Figure 8: Power BI dashboard 1

The first dashboard presents a Power BI visualisation combining a Pie Chart, Treemap, Table, and Gauge to summarise population-related values by year and category, highlighting an aggregated predicted population of 47.90M, as shown in Figure 9.

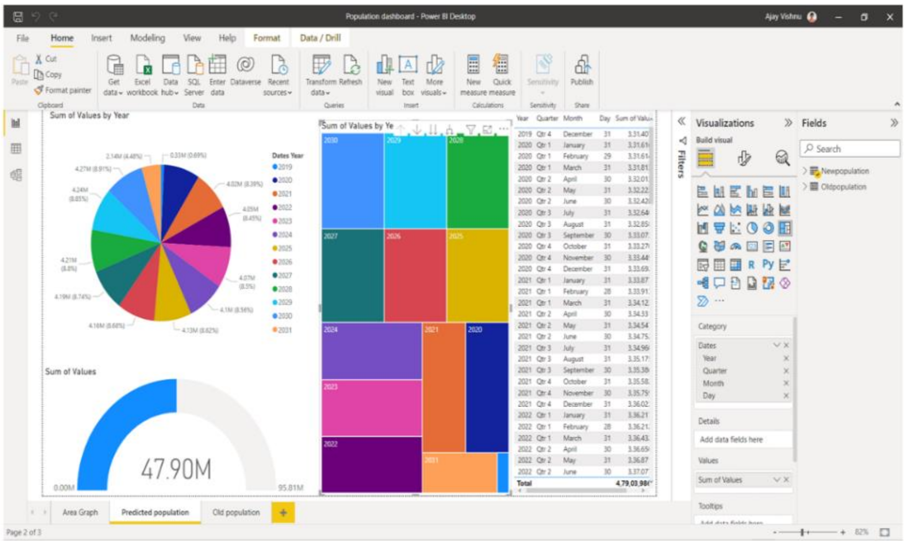

Figure 9: Power BI dashboard 2

The second dashboard extends the analysis with a more granular doughnut chart, a denser treemap, detailed tabular breakdowns, and a gauge indicating a higher overall population of 199M, demonstrating comparative growth patterns as illustrated in Figure 10.

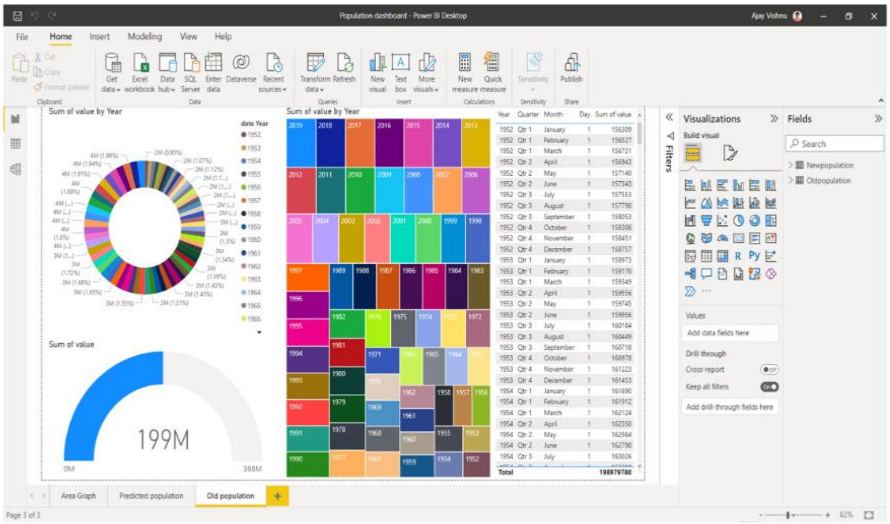

Figure 10: Power BI dashboard 3

6. Conclusion

Because Prophet is so easy to use, it is a great base model for breaking up your time series into simple time parts. But if your signal is noisy, it can be hard to get the model to work better. If your time series matches particular business cycles, you can get extremely good results rapidly without having to do a lot of feature engineering. But the trend part isn't always well estimated, which can lead to big changes in performance. Because of this, this model may need to be watched closely and changed often by people. So, population forecasting works and is shown to the user. And we've finished all of our goals. Prophet is a great tool for making rapid and accurate forecasts. It features easy-to-understand settings that a person with a lot of information about the subject but not a lot of technical abilities in predictive modelling may change. Readers can also try fitting Prophet straight to hourly data and talk about it in the comments to see if they achieve a better outcome.

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Conflicts of Interest Statement: The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Ethics and Consent Statement: All authors have reviewed and approved the final version of the manuscript and provide their full consent for its publication and dissemination for scholarly and educational purposes.

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