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1. Introduction

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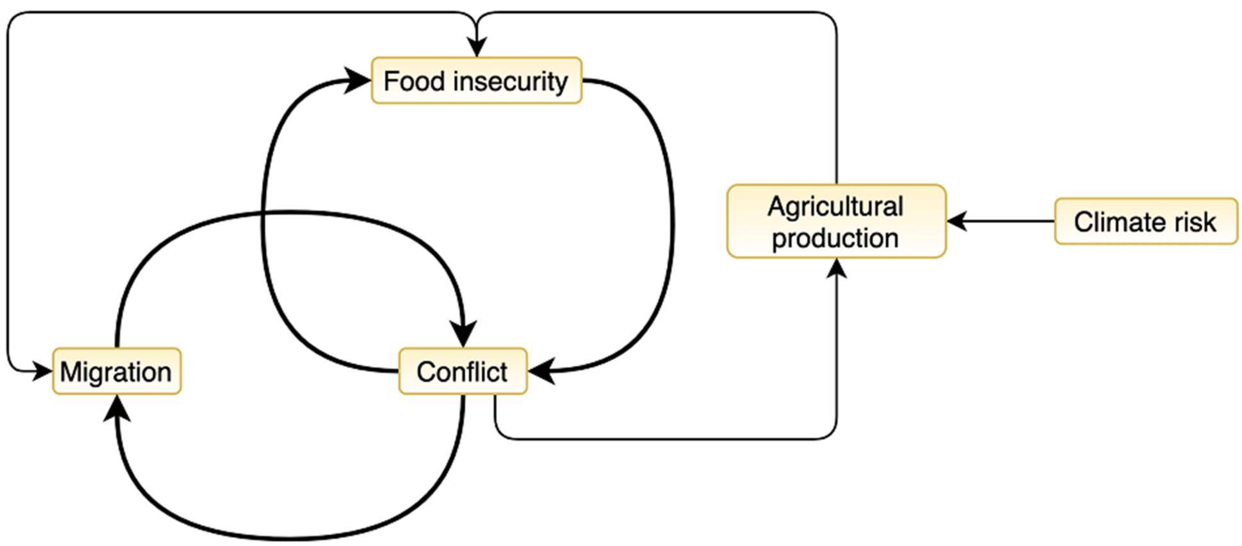
1.1 Background on Global Food Insecurity

The issue of food insecurity in the world has remained a serious bother to the world health as millions of people are affected particularly in conflict-affected regions. According to the report by Abdullahi, Kalengyo and Warsame (2024), approximately 828 million individuals experienced undernutrition in 2021, and the issue was aggravated by various factors, among which are conflict, economic instability, and climate change. Wars, especially, are very important as they disrupt production of foods, destroy distributions channels and cause individuals to relocate. Such uprooted groups end up relying on humanitarian aid which even though necessary, only helps to prolong the crisis instead of ending it. Food insecurity has become a vicious cycle worsening conflict and vice-versa, which can be seen in such countries as Yemen, South Sudan, and Syria, as they experience severe food insecurity. Regardless of the international concerns, including the aims of the UN, which is supposed to eradicate hunger by 2030, the situation in the areas of the documented conflicts is slow. In order to reduce this emerging problem, timely and correct data collection and forecasting is essential.

1.2 Importance of Forecasting in Conflict-Prone Regions

Projection of food insecurity in conflict prone areas is a crucial tool of responding to humanitarian emergencies promptly and efficiently. According to Kemmerling, Schetter and Wirkus (2022), the consequences of conflicts are fast and unforeseeable food security changes, caused by agricultural production, supply networks, and massive displacement. Other traditional forecasting techniques are ineffective in such settings since there is no trusted information, and conflict is volatile. Forecasting can be done accurately enabling governments and organizations to identify arising crisis before they get out of control. Taheri Hosseinkhani (2025) highlights that the sooner the food insecurity is detected, the more suitable interventions can be organized, including pre-positioning the food stocks and establishing distribution channels. Moreover, the realization of food insecurity cycling in conflict zones as observed in Figure 2 assists in knowing the high-risk times of a particular action.



7 *Figure 1: The Cycle of Conflict and Food Insecurity; Source: (Planetary Security Initiative, 2020)*

37 Forecasting can be used to provide a sustainable solution to food insecurity in such regions by
24 incorporating both short-term and long-term solutions as shown in Figure 2.

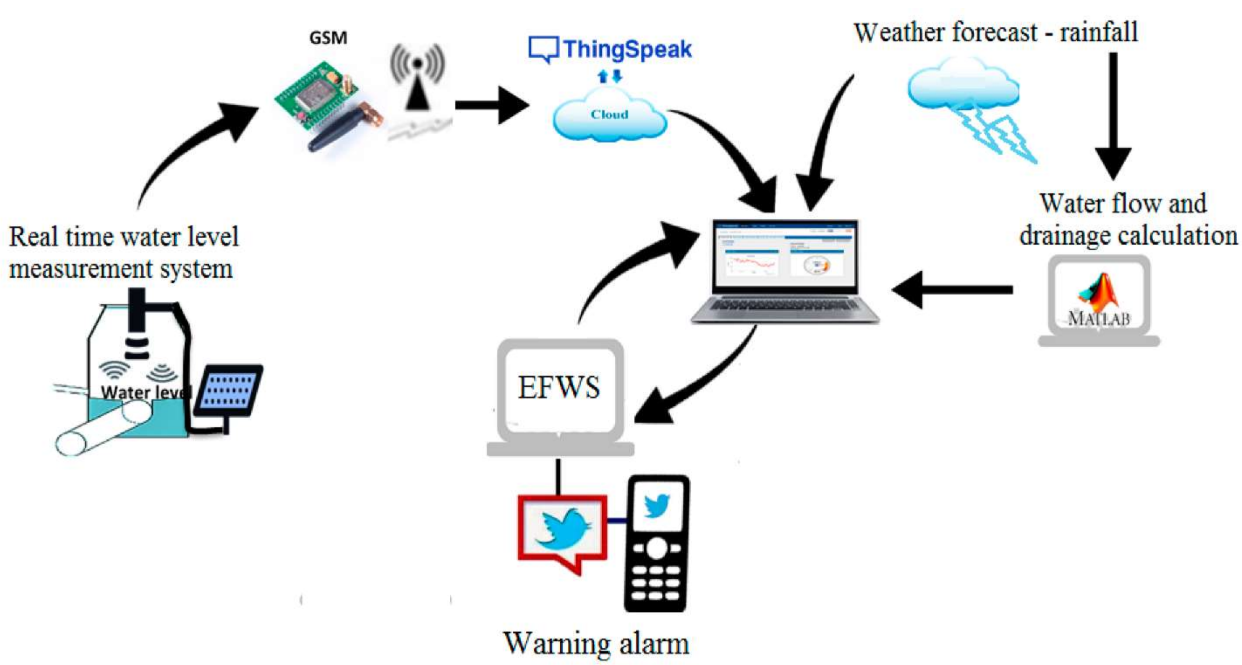


Figure 2: Framework for Early Warning Systems Based on Forecasting Models; Source: (Alasali et al., 2021)

1.3 Role of IPC Phase 3+ Data and AI Integration

The Integrated Food Security Phase Classification (IPC) is critical in the detection and management of food insecurity particularly in conflict-stricken regions. According to the IPC (2021), Phase 3+ is a crisis in which there is a life threat of food insecurity. This information can be used in such areas to prioritize and redirect funds to the most vulnerable. According to Tambo et al. (2023), it is essential to pay attention to this stage. The use of combination of AI systems such as Long Short-Term Memory (LSTM) networks and Prophet has been effective to enhance forecasting. According to research conducted by Meckawy et al. (2022), it is possible to make the models more accurate and improve early warning systems and timely interventions.

2. Aims, Objectives, and Research Questions

2.1 Research Aim

The main objective of this dissertation is to examine and predict the trends of food insecurity in places with high risks of conflicts, based on the statistics of Integrated Food Security Phase Classification (IPC) system and time-series forecasting methods. This paper will attempt to gain a better comprehension of the causes of food insecurity in conflict areas and assess how AI models, including Long Short-Term Memory (LSTM) networks and Prophet can enhance the quality of food insecurity projections.

2.2 Research Objectives

To achieve this aim, the following specific objectives will guide the research:

- Investigate the evolution of food insecurity levels in conflict-prone regions using IPC Phase 3+ data, identifying key periods of crisis and patterns in food insecurity over time.
- Utilize both traditional models, such as ARIMA and SARIMA, and AI-based models like Prophet and LSTM, to predict food insecurity levels for the years 2024 and 2025.
- Assess and compare the forecasting accuracy of ARIMA, SARIMA, Prophet, and LSTM models using performance metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

- Provide actionable recommendations for policy makers and humanitarian organizations based on forecast results, highlighting areas at greatest risk and proposing potential interventions to mitigate food insecurity.

2.3 Research Questions

To guide the research, the following research questions will be addressed:

- What are the key drivers of food insecurity in conflict-prone regions, and how have these trends evolved from 2017 to 2025?
- How accurate are traditional forecasting models (ARIMA, SARIMA) compared to AI-based models (Prophet, LSTM) in predicting food insecurity levels in these regions?
- What actionable insights can be derived from these forecasts to inform humanitarian interventions and policy in conflict zones?

3. Literature Review

One of the most topical problems all over the world is food insecurity, especially in the conflict-torn areas. Armed conflicts, economic instabilities, climate change and governance problems tend to combine and worsen food insecurity in such areas causing massive suffering. It is important to predict food insecurity in these regions to have timely actions and proper allocation of resources.

3.1 Food Insecurity and Its Impact

Food insecurity is often understood as the inability to have regular access to enough and healthy food to have an active and healthy life (Sumsion, June and Cope, 2023). According to Gebrihet, Gebresilassie and Gebreselassie (2025), food insecurity affects more than 820 million individuals globally, and the problem is more pronounced in war-affected and post-war countries. Besides ruining food production and distribution systems, war results in displacement, increased poverty, and exposure to more environmental shocks (Ben Hassen and El Bilali, 2023). This has been most notable in such countries as Syria, Yemen, and South Sudan where there have been continuous violence situations resulting in serious food insecurity crisis.

3.2 Forecasting Food Insecurity: Traditional Approaches

Conventional food insecurity forecasting techniques have been mainly based on the theoretical models, including the ARIMA and SARIMA. AutoRegressive Integrated Moving Average (ARIMA) is a time-series model, which forecasts future values according to previous data. ARIMA has been applied to predict an economic environment quite extensively, and to some extent, it has been applied to forecast food insecurity because it is capable of modeling trends and seasonality (Herteux et al., 2024). Mahaluca, Carsane and Vilanculos (2025) predicted agricultural yields using ARIMA, as an example, which is directly related to food insecurity. The strength of ARIMA is that it is able to capture the short-term trends, when the data is stationary (i.e., the statistical characteristics do not vary with time). Nonetheless, ARIMA performs poorly when there are more complex and non-linear relationships or other external shocks like conflict or climate change, cause major deviation of normal patterns.

In order to overcome the problem of seasonality, SARIMA (Seasonal ARIMA) was created, which adds the seasonal factor to the model. This has been of benefit in agricultural forecasting where seasonal changes are a major factor in the food security (Wanjuki, Wagala and Muriithi, 2021). As an example, Mohale and Obagbuwa (2024) used SARIMA to predict African crop yields, which shows that the model is capable of predicting seasonal trend of food insecurity within rural agricultural settings. Even though the SARIMA models are stronger to consider seasonality, it has the drawback of being unable to consider unexpected shocks, including the conflicts or natural calamities.

3.3 Emergence of AI-Based Forecasting Models

Artificial intelligence (AI) and machine learning (ML) models have become increasingly trendy in predicting food insecurity in recent years because they can process large and complex datasets and non- linear relationships. Among them, Prophet and LSTM have become the significant tools of time-series forecasting.

Prophet is an open-source application created by Facebook to predict time-series data that have great seasonal variations and a considerable missing data (Rafferty, 2023). It especially fits well in cases when data has seasonal variations e.g. agricultural production, which has a direct relationship to the food insecurity. Al-Hasani and Al-Qaraguli (2025) used Prophet to model food security in conflict areas and demonstrated that it can deal with irregularities and seasonal patterns. The flexibility is one of the most important advantages of Prophet as it can accommodate the effects of holidays and other outside forces, which will be useful in capturing the effects of events such as conflicts, which can affect food systems in an unpredictable manner.

23 A variant of recurrent neural network (RNN), LSTM (Long Short-Term Memory) has also demonstrated itself as a successful method of predicting time-series data long-range patterns. The
38 LSTM models are most effective in long-term dependencies and are therefore most suitable in predicting food insecurity where the effects of conflicts and other externalities are usually delayed. The LSTM was used to predict the prices of food in conflict prone areas, and the research Herteux et al. (2024) showed that the LSTM could capture the lagged impact of conflict and seasonality. Learning and adapting to the non-linear and complex patterns of the data is the biggest benefit of LSTM as compared to traditional models and it makes it a potent tool in predicting food insecurity in unstable areas.

3.4 Comparison of AI and Traditional Models

A number of studies have compared conventional forecasting models with AI-based ones and show
39 the benefits of machine learning when handling complex, non-linear data. Dubey et al. (2021) compared ARIMA, SARIMA, and LSTM when applied to forecast economic factors and established that LSTM performed better than the traditional models, especially when it comes to non-linear relationships. In a similar fashion, Saqware and Beary (2023) discovered that machine learning models, such as Prophet, were more precise than ARIMA in predicting food prices and production amid conflict areas. Although AI models have been shown to be more useful in addressing the intricacies of real-life data, they are also highly resource-consuming in terms of computation and also demand much data to train. This difficulty explains why it is essential to develop AI techniques alongside expert knowledge to make the forecasts accurate and feasible.

3.5 Limitations and Gaps in Literature

Irrespective of these positive outcomes, there are a number of weaknesses in the use of forecasting models to food insecurity. Among the major weaknesses is the fact that there is no high standard of data in conflict prone areas. The data on the IPC that is being utilized in most studies is usually incomplete, with some of the cases being missing or inconsistency in reporting. Moreover, conflict can usually make the data gathering process complicated, such that gathering real-time information is hard to be reliable. Deléglise et al. (2022) note that enhancing data collection and data reliability in datasets are important to enhance the accuracy of food insecurity predictors.

The other area of a literature gap is the combination of different forecasting models. Although conventional models such as ARIMA and SARIMA have generally been popular and AI models such as Prophet and LSTM are on the rise, there is limited literature of the two models as compared to each other as a predictor of food insecurity. Wu and Levinson (2021) indicate that the
4 combination of a statistical and machine learning model, which is known as an ensemble approach, has the potential to enhance forecast accuracy since both approaches are strong in their respective strengths.

41 **4. Methodology**

4.1 Research Philosophy

19 This dissertation will adopt a positivist philosophy, which assumes that an objective reality exists and can be measured, observed, and predicted. Positivism, as described by William (2024), emphasizes the use of scientific methods to gather quantifiable data and identify patterns or causal
5 relationships. In the context of food insecurity forecasting, this philosophy aligns with the study's focus on quantitative data and statistical modeling to predict future trends. Zellner et al. (2021) argue that positivist approaches are effective for testing hypotheses using historical datasets, enabling the objective evaluation of forecasting models. This research will use the IPC dataset and
36 apply statistical and machine learning models like ARIMA, SARIMA, Prophet, and LSTM to predict food insecurity in conflict zones.

43 **4.2 Research Approach**

The research approach for this dissertation is deductive, where an existing theory or hypothesis is
48 tested against specific data. As Fife and Gossner (2024) explains, a deductive approach begins with a theoretical framework, using data to either confirm or challenge the hypothesis. In this study, the hypothesis is that both traditional statistical models and AI-based forecasting models

can accurately predict food insecurity trends in conflict-prone regions. By applying these models to historical data, the study will evaluate their ability to forecast food insecurity and assess the accuracy and validity of the predictions they generate.

4.3 Research Strategy

The research method adopted in the study will be quantitative. The research will be aimed at the analysis of numerical data devoted to the problem of food insecurity in conflict-prone regions and the IPC (Integrated Food Security Phase Classification) dataset will be studied in particular. The information shall be utilised to construct and test prediction models. The quantitative method provides the opportunity to use statistical tools and methods to generate objective and measurable results. Forecasting models shall be used to establish patterns, trends and predict how much food insecurity will be in the future. The results of the study will rely on the performance of the models compared in terms of such indicators as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

4.4 Research Method

This research will employ a computational modeling method. The core methodology involves the following key steps:

1. **Data Collection**: IPC dataset (World Bank, 2021) will be used as the main source of data. It contains details about food insecurity statuses in 52 countries that are prone to conflicts including 2017 to 2025. This data consists of the data on IPC Phase 3+, which is the number of individuals facing food insecurity at the level of crisis. The data will be obtained on the Data360 platform of the World Bank and will be obtained in CSV format or through API and processed with ease.
2. **Data Preprocessing**: Data preprocessing will include missing values, data inconsistencies, conversion of dates into standard format, and aggregation of the data to monthly level so that the data can be compatible with the time series forecasting models.
3. **Model Development**: The developed forecasting models (ARIMA, SARIMA, Prophet, and LSTM) will be used on the preprocessed data. The models would be trained and validated with the help of historical data (2017-2020) and tested on the unseen data (2021-

2023). The performance measures that will be used to evaluate the models include RMSE and MAE.

4. **Model Comparison**: The models will be compared, having been trained and validated, in terms of their performance on the test set. The comparison would be based on the type of model that gives the best and solid predictions of food insecurity in the conflict zones.
5. **Interpretation of Results**: The results will be interpreted based on evaluation of the most effective forecasting model to predict food insecurity in conflict-prone regions based on the performance comparison. The findings will then be utilized in giving policy proposals to the humanitarian organizations.

18 **4.5 Time Horizon**

The study will use cross-sectional time of analysis of the food insecurity trends. The dataset under consideration represents the time period between 2017 and 2025. This can be used to analyze the historical trend in terms of 2017-2020 to train the models and predictive forecasting in 2021-2025 to appraise the future trend. It will prioritize the levels of food insecurity in 1-2 years (2024-2025) to be predicted, which is vital to humanitarian planning and resource distribution. The study will take into account the changes over long-term, along with the seasonal changes, to measure the possibility of the continuing or reoccurring food insecurity crises.

4.6 Techniques and Data Collection

The study will utilize several computational techniques and tools to ensure robust data analysis and accurate forecasting. These include:

40 • **Statistical Analysis**: The data will be first explored by using the Descriptive statistics in order to generalize the central tendencies, variability, and distributions of the food insecurity levels in the dataset.

45 • **Time-Series Analysis**: In time-series forecasting methods, the application of ARIMA, SARIMA, Prophet, and LSTM models will be used to forecast the level of food insecurity in the future.

11 35 • **Machine Learning**: The study will also engage the training of AI-based models such as
20 Prophet and LSTM to deal with complex, non-linear relationships and long-term

dependence in the food insecurity data since such models have been demonstrated to be superior to traditional statistical tools in other predictive tasks.

Table 1: Potential Advantages of AI Models over Traditional Models for Forecasting Food Insecurity

Aspect	**Traditional Models (ARIMA, SARIMA)**	**AI Models (LSTM, Prophet)**
Model Type	Linear models, suitable for stationary data with a clear trend or seasonality.	Non-linear models, suitable for complex, dynamic, and non-linear data patterns.
Handling Non-Linearity	Struggles with non-linear data patterns, especially in conflict-driven crises.	Well-suited for capturing non-linear relationships and sudden shifts in data.
Seasonality Handling	Can handle seasonality with SARIMA, but struggles with irregular seasonal patterns.	Excels at capturing and forecasting complex seasonal patterns (e.g., Prophet's seasonal effects).
Long-Term Dependencies	Limited ability to capture long-term dependencies (focuses more on short-term).	LSTM excels at modeling long-term dependencies and temporal dynamics over extended periods.
Adaptability to External Shocks	Struggles to account for external shocks, like conflicts or natural disasters.	AI models, especially LSTM, can adapt to external shocks and quickly adjust predictions.
Data Requirements	Requires stationary data and works best when the data shows consistent patterns.	Can handle irregular, incomplete, or missing data and still provide accurate forecasts.
Complexity of Model	Simple to implement and computationally efficient for small datasets.	More complex to implement but offers superior performance with large and complex datasets.
Real-Time Adaptability	Limited real-time adaptability in response to sudden changes in data trends.	AI models like LSTM can adapt to real-time changes in food insecurity data effectively.

4.7 Research Materials and Instruments

The analysis will not involve design of primary data collection tools (questionnaire or interviews) since the research will only use secondary data (IPC dataset). Nevertheless, the tools and methods that will be necessary to this research will include the following:

- **Forecasting Models**: Python and other libraries, eg, statsmodels, Prophet, and TensorFlow to LSTM modeling, will be used to build and train the models.
- **Data Visualization Tools**: Matplotlib and Seaborn will be employed to present the results of the forecasting models such as time-series plot, heatmap, and model comparisons diagrams.
- **Performance Metrics**: Calculation of RMSE and MAE tools will be incorporated in the model evaluation in order to provide a quantitative measure of the models accuracy.

4.8 Ethical Considerations

The data used in this research are regularly available to the public and, hence, ethical issues mostly deal with ensuring the transparency of the information and its responsible utilization, as well as with the recognition of the data sources. The study will follow the ethical standards as it will:

1. **Transparency**: The sources of all the data will be openly recognized, and all preprocessing steps or assumptions will be openly described in the methodology.
2. **Responsible Use of AI**: AI models will be utilized in a non-bias manner and caution will be taken to make sure that any predictions that are provided by AI models are transparent and understandable to the stakeholders.
3. **Data Privacy**: Since the dataset is open source, there will be no issues with the privacy of individuals. Nevertheless, when future datasets are used, the confidentiality and privacy of data will be observed.
4. **Accountability**: The results of the AI-driven predictions will be reported with full accountability to avoid the misinterpretations and misuse of the forecast in policy and humanitarian decision-making.

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Table 2: Summary of Traditional and AI-Based Models for Food Insecurity Forecasting

Model Type	Model Name	Key Features	Advantages	Limitations
Traditional Models	**ARIMA**	Autoregressive Integrated Moving Average, used for univariate time-series data.	Simple to implement and computationally efficient for small datasets.	Struggles with non-linear relationships and external shocks, requires stationary data.
	SARIMA	Seasonal ARIMA, an extension of ARIMA that accounts for seasonal patterns.	Suitable for datasets with clear seasonal cycles, captures seasonality.	Still struggles with non-linear patterns and irregular seasonal data, not ideal for conflict zones.
AI-Based Models	**Prophet**	Open-source forecasting tool by Facebook, handles seasonality and holiday effects.	Effective in capturing non-linear patterns, irregular trends, and missing data.	May require more computational resources and fine-tuning for optimal results.
	LSTM	Long Short-Term Memory, a type of recurrent neural network (RNN) for sequential data.	Captures long-term dependencies, adapts to complex, non-linear data patterns and external shocks.	Complex to implement, requires large datasets and significant computational power.
Hybrid Models	**Ensemble Models**	Combining multiple forecasting models (traditional and AI-	Leverages strengths of both traditional and AI models to enhance prediction accuracy.	More computationally expensive and complex to implement.

		based) for better accuracy.		

5. Research Plan (Gantt Chart)

The study project will be introduced in the form of a Gantt chart, which will contain all significant activities with the corresponding deadlines. The activities will be distributed across 12 weeks, with the activities being confined to those activities pertinent to the dissertation which include data collection, preprocessing, model development, training, validation and writing of the report.

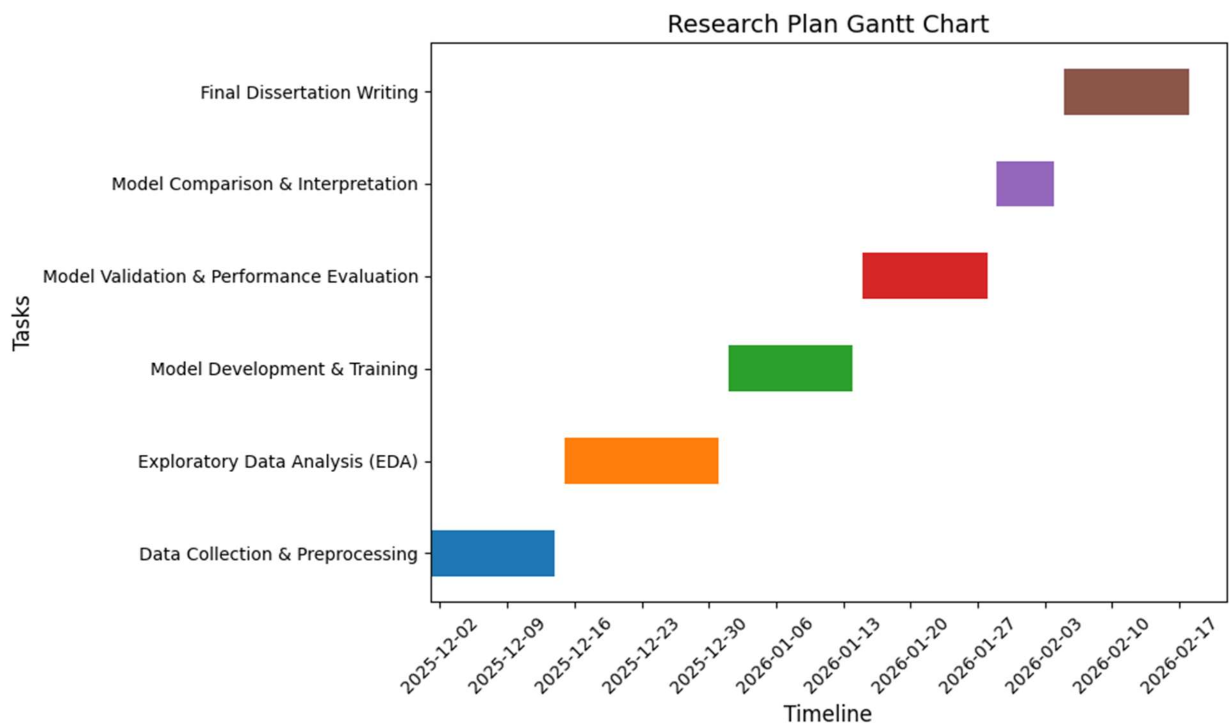

Figure 3: Gantt Chart

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