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Bhabanipur Assembly Election Digital Twin: A GEO-Spatial Multimodal Artificial Intelligence Structure

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Abstract—

Constituency-level election prediction is difficult given the dynamic, non-linear and complex nature of voting behavior that is shaped by behavioral profiles, spatial variance, emotional narratives and temporal variations. Traditional approaches, such as opinion polls and static statistical analyses, often fail to capture these changes in real time. This study suggests the Bhabanipur Assembly Election Digital Twin as a nascent multimodal geo-spatial digital phenotyping approach that will create a digital twin of the constituency by dynamically building a virtual model of the constituency from publicly available digital data sources.

This system integrates multiple data sources to create a predictive model, incorporating search trends, social media data, news sentiment, and historical voting records. Our methodology applies recent advances in social media analytics and computational social science to model voter dynamics through a Voter Stability Index (VSI) that measures support volatility and stability. Spatial intelligence is integrated using geofenced micro-zone mapping for constituency segmentation based on location-based signals. Natural Language Processing (NLP) techniques, including sentiment polarity and emotion detection, are used to capture the language and emotion. These tools are enhanced with transformer-based and lexicon-based methods. Time-series forecasting techniques such as Long Short-Term Memory (LSTM) networks are used to model the time evolution of voter preferences, while ensemble learning methods, such as Random Forest, are used to capture the nonlinear

relationships in the multimodal data.

The different elements of the system are integrated into a total predictive model called the Total Election Winning Probability Index (TEWPI), continually updating the likelihoods of voting outcomes. This system, which uses multimodal fusion, geo-spatial intelligence and predictive intelligence, simulates the spatial-temporal evolution of voter choices. This Digital Twin enables real-time scenario analysis, early detection of sentiment shifts, swing zone identification, and pre-electoral forecasting of the winner.

The proposed approach highlights the integration of multimodal AI and digital phenotyping with geo-spatial intelligence to transform traditional election analysis into a predictive, adaptive and data-driven early warning system. This study contributes to the emerging literature on the interconnections of political data science, artificial intelligence, and smart governance by offering a scalable framework for predicting elections on a constituency level without relying on real data collection.

Keywords— Election Prediction, Digital Twin, Multimodal Machine Learning, Geospatial Intelligence, Natural Language Processing, Time-Series Forecasting.

I. INTRODUCTION

It is still to be resolved in data-oriented governance and in political science that there is problematic electoral forecasting and prediction. The current surveys and statistical projections that are long and partial procedures cannot usually keep up with the fast changing preferences and voter trends. These restrictions dilute their capacity to replicate the complexity, richness and depth of voter behaviour, in complex districts especially [1][2].

With the continued creation of digital platforms, the proliferation of behavioral data that is availed by social media and other online endeavors has become a significant proxy when it comes to determining the opinion of the people. Even as early as 2013, part of the initial research work has revealed that the use of social media, particularly social networking platforms such as Twitter, may be effectively utilized to follow the election patterns and draw conclusions [3][4]. Future research has shown that machine learning-based emotion translation of online conversations can be employed in order to induce considerable effect on predictive strength [5], [6]. Most of the existing strategies are, however, founded on the information of a single medium, and they cannot unify spatial and temporal features.

Nevertheless, in the recent years, there is an advancement in computational social science and the modeling of digital behavior that has shown that it is possible to infer individual preferences and behavioral dispositions based on large digital data sets [7][8]. These developments combined with the further development in Natural Language Processing (NLP) have led to the possibility of detecting certain emotional and cognitive signals of information presented in text that improves our understanding of the public opinion [9][10]. On the same note, attention mechanisms and other forms of transformer model have also helped in understanding and processing languages [11].

Meanwhile, multimodal machine learning also has proved itself to be a powerful approach to integrating different sources of data. "It can be seen that multimodal strategies are more effective in prediction tasks than unimodal ones, and these strategies are based on the integration of various types of text, behavior and context information [12]-[15]. Despite these developments, these are still not highly utilized on prediction of elections particularly on constituency level.

Another significant aspect in election prediction is the geospatial intelligence. The concept of citizen as sensors underlines the importance of spatial data to the analysis of events and trends of behaviour in the real world [16]. The value of spatial data is also of interest to urban computing to define functional boundaries and diverse behaviour in urban areas [17][18]. Nevertheless, geospatial micro-segmentation is rarely used in modern algorithms used in forecasting elections, and thus, these algorithms cannot determine swinging regions.

In addition, voter intentions are highly dynamic and based on the election campaigns, social and economic conditions and others. The time-sequencing data which seeks to compute the temporal correlation and predict the dynamics of time-sequenced data has been done using LSTM networks and time-series techniques [19],

[20]. Some machine learning approaches such as the Random Forest also result in better predictions with non-linear interactions between the features [21].

To address them, this research proposes the model of the Bhabanipur Election Digital Twin to be a new and multimodal geospatial digital phenotyping platform that simulates a virtual system of the constituency. It uses the voter behavior measures (Voter Stability Index) founded on the Voter Stability Index (VSI), geospatial segmentation founded on geofencing, emotion and language-based segmentation founded on Natural Language Processing (NLP) and time-based segmentation founded on time-series modeling.

The novelty of such an approach is the Total Election Winning Probability Index (TEWPI) which utilizes different kinds of input data. The proposed system exploits the publicly accessible digital information, eliminating the need to gather data on the field, and allows it to be scaled and modified. It allows the system to predict the outcome of the elections immediately when the dynamics of the preferences of the voters is changing in time and space, it discovers significant factors that contribute to the shift in voter preference and overall prediction of the outcome of the elections.

Contributions of the Paper

1. Presents a new Election Digital Twin real-time prediction of elections at the constituency using data, and overcoming the constraints of traditional forecasting models [1] -[4].
2. Suggests the use of the Voter Stability Index (VSI) as a means of simulating voter behaviour using support consistency, and volatility with the assistance of digital traces [7], [27], [28].
3. Brings in geospatial micro-zoning in the form of geofencing to identify local voting and swing locations to fill in the gaps of the existing election prediction systems [17]19].
4. Trains a multimodal artificial intelligence system, which integrates behavioral, textual, spatial, and time-based information to enhance the accuracy of prediction [13]-[16].
5. Learned to read subtle voter sentiment on textual data by using high-level NLP (sentiment, emotion analysis, transformer models) [9]–[12].
6. Relies on time-series forecasting (LSTM) to predict the time-changing voter preference dynamically [20], [21].
7. Raises the Total Election Winning Probability Index (TEWPI) as a single predictive measure by means of ensemble learning to get strong predictions [23].
8. Gets rid of the necessity to work with physical surveys, which allows it to be scaled and effective by using digital phenotyping and publicly available data [30], [31].
9. Supports real time simulation and early detection of swing factors and this is better than the fixed model in the proactive analysis of elections [32].
10.Brings about AI-based political analytics and intelligent governance, which is endorsing the multimodal intelligence to be embraced in the electoral systems [33], [34].

II. LITERATURE REVIEW

Election prediction has long been a subject of focus for political science, statistics and computational intelligence. Traditional approaches to forecasting election outcomes are primarily based on opinion polls, survey techniques and statistical models. These methods can provide basic information but often have issues with statistical sampling error, time delays in collecting data and model inflexibility to changing attitudinal data [1], [2]. Many approaches to poll aggregation have been suggested in order to enhance the accuracy of predictions; however, they still heavily depend on fixed and structured data, and are not flexible enough to adapt to changing voting patterns of elections.

The rise of the internet has led to a key role for social media in sentiment analysis. Early work has shown that the ability to predict election results from user-generated data, for example from the social platform Twitter, can be achieved by analysing sentiment and interaction patterns [3], [4]. Follow-up research also demonstrated that the use of sentiment analysis can be enhanced by using machine learning methods for prediction [5], [6]. However, these models only consider single-modality text and cannot reflect multi-aspect factors of voter behavior, including the temporal and spatial patterns of the electoral process.

To overcome the drawbacks of these methods, Natural Language Processing (NLP) has been extensively used for sentiment and emotion analysis of political text. Dictionary-based methods provide meaningful sentiment scores, and more sophisticated models, such as transformers, can understand a deeper semantics of texts

[7][12]. While these developments have improved our understanding of electoral systems, the majority of NLP-based election prediction systems primarily consider text sentiment, and fail to capture behaviour patterns and spatial variations that impact voter interactions.

On the other hand, computational social science has recently begun to support macro understanding of human behaviour using digital traces. Online activities have been shown to predict preferences, personality and decision making styles [27], [28], and help understand voter preferences. Digital phenotyping approaches extend this further by tracking these indicators to facilitate the dynamic modelling of human decision making [29], [30]. These methods use behavioural data for predicting elections; but they have not been extensively studied alongside geographical and temporal analysis.

Multimodal machine learning is attracting a lot of attention these days for combining multiple sources of information. Multimodal methods incorporating textual data, contextual data and behavior data have been shown to outperform unimodal methods [13]-[16]. Multimodal learning with tensor fusion and deep multimodal neural networks allows for the extraction of more complex relationships between multimodal data. But multimodal methods for predicting electoral results are still in their early phases, especially at the constituency level, where detailed analysis is needed.

Geospatial intelligence is important for local voting. The idea of "citizens as sensors" also highlights the role of geospatial data in event modelling [17]. City computing also offers lessons on how spatial data can be used to determine functional zones of cities, allowing for the detection of behaviour clusters and patterns [18], [19]. Despite these developments, existing election models tend not to include geospatial micro-zoning, which can be used to identify swing states and voting trends, shown in Figure 1.

Figure 1: Spatial variation of voter behavior across the constituency highlighting strong support, swing regions, and opposition zones.

The temporal dimension of voter behavior has also been explored using time-series analysis. Traditional statistical models such as ARIMA have been widely used for trend forecasting, while deep learning approaches such as Long Short-Term Memory (LSTM) networks have demonstrated superior performance in capturing sequential dependencies [20], [21]. These models enable the analysis of sentiment evolution and campaign impact over time. However, most existing studies treat temporal modeling as an isolated component rather than integrating it with behavioral and spatial features,as shown in Figure 2.

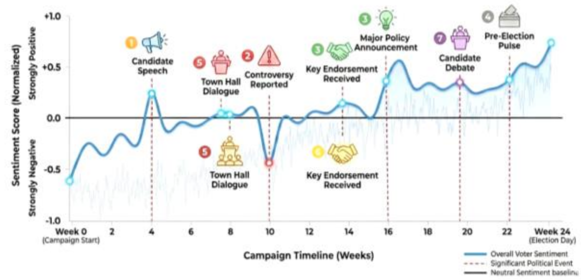

Figure 2: Temporal evolution of voter sentiment showing observed trends and smoothed patterns with event-driven variations over time.

Machine learning and ensemble algorithms such as Random Forest have been widely applied to election studies both in prediction and classification [23]. They are quite good at non-linear and high-dimensional data capture. However, the individual machine learning models are not explainable and cannot incorporate domain knowledge (behavioral and geospatial patterns) into their models. More sophisticated methods that merge both the statistical learning theory [24][26] and the predictive analytics theory [31] have attempted to address these issues, but there is no framework, which would address all these variables in a systematic manner.

Predictive modelling of election outcomes has also not been left behind in the development by big data analytics. Social media analytics and other data processing techniques can be used to analyze the opinion of the people in real-time and the voter turnout [32], [33]. It is also observed that the digital channels are also important in the political process and therefore there is a need to establish efficient analytical tools that can effectively manipulate different sources of information [34]. There have been proposed alternative visual analytics and the use of dashboards to facilitate the perception and decision-making [35]. The techniques however are inclined to favour the representation rather than prediction as observed in Figure 3.

on over predictive modelling as shown in Figure 3.

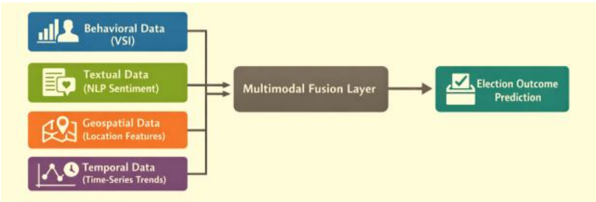

Figure 3: Multimodal data integration pipeline combining behavioral, textual, geospatial, and temporal data and predicting the outcome of elections.

In general, the existing literature shows significant improvement in the application of social media analytics, natural language processing, machine learning and geospatial algorithms to predict elections. Nevertheless, the current techniques have their flaws in single-modality data, as well as in the degree of combination of spatial and temporal data and real time modeling. There can be seen a vacuum in the literature on the development of a comprehensive system, which will involve behavioral modeling, multimodal data integration, geospatial, and temporal techniques.

The suggested solution will help fill these gaps by bringing the Bhabanipur Election Digital Twin, or a blend of knowledge around computational social science, multimodal machine learning, geospatial analysis, and time-series modeling, to one predictive system. Having all these elements, the proposed system will strive to address the shortcomings of the current practices and offer a scaled, real-time, and information-driven remedy to the issue of forecasting the outcomes of the election process on the constituency scale.

III. METHODOLOGY

The proposed Bhabanipur Election Digital Twin (EDT) is a multidimensional, spatial, and temporal prediction system designed to dynamically model election results at the constituency level. It treats voter intention as a dynamic temporal process that changes over time by combining multiple streams of data such as behavior, text, space and time. The proposed approach uses publicly available digital data to enable dynamic and flexible election result prediction, instead of the traditional approach that relies on static data and survey-based methods at fixed points in time [1], [2].

The proposed system architecture is in the form of a multi-layered pipeline comprising data collection, preprocessing, feature extraction, multimodal data fusion, machine learning, and decision making. The system architecture should be illustrated in figure 4, in which the different sources of data, such as social media, media sites, google trends, and historical data, are represented as nodes. The input is processed by preprocessing and feature extraction units (VSI, NLP, geospatial, temporal) and then fused in multimodal fusion. This is sent to machine learning models for analysis, followed by the final prediction step using the Total Election Winning Probability Index (TEWPI). The figure should be in left-to-right progression, with distinct and labelled segments and flow arrows.

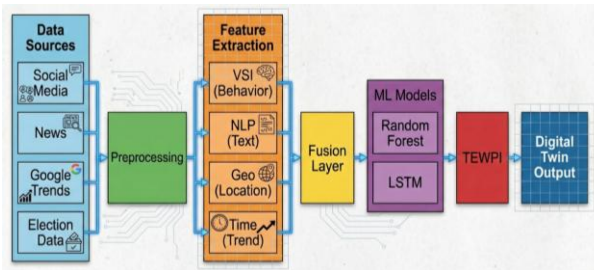

Figure 4: System Architecture of the Proposed Bhabanipur Election Digital Twin Framework

B. Data Acquisition and Preprocessing

The system gathers data in a myriad of publicly available data such as social media data, news articles, search engine trending and election statistics of past elections. This data collection relies on the approach of computational social science whereby big data is used in studying human behavior and preference [27], [28]. The following data can be stated:

$D = \{D_b, D_t, D_g, D_s\}$

Where D_b denotes behavioural data, D_t textual data, D_g geospatial data and D_s temporal data

The preprocessing stage involves noise removal, tokenization, normalization, and temporal alignment. Textual data is cleaned by removing stopwords, special characters, and irrelevant symbols, while numerical features are normalized using min-max scaling:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Geo-tagged data is mapped to spatial coordinates, and timestamps are synchronized to ensure consistency across modalities.

C. Feature Extraction

a) Behavioral Modeling using Voter Stability Index (VSI)

To quantify voter behavior, the proposed framework introduces the Voter Stability Index (VSI), which captures both the consistency and volatility of voter preferences over time. VSI is defined as:

$$VSI_i = \alpha S_i + \beta F_i + \gamma V_i$$

where S_i represents sentiment consistency, F_i denotes engagement frequency, and V_i indicates opinion volatility. The parameters α, β, and γ are weighting factors learned during model training.

Figure 5 is expected to depict the manner in which VSI will perform with time, where the x-axis depicts the time and the y-axis depicts the values of VSI. There should be a number of curves representing stable voters (low variance), swing voters (moderate fluctuations), and volatile voters (high variance) that need to be taken into consideration in the graph and how voter stability is dynamically evolving.

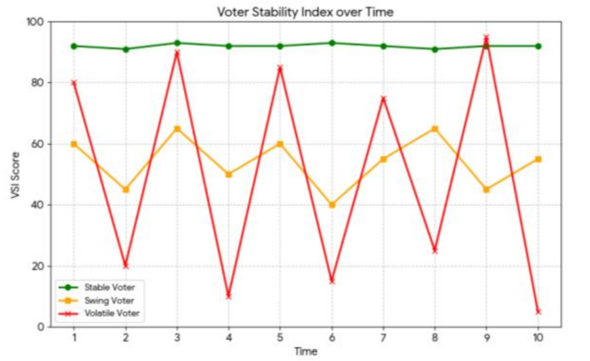

Figure 5: Voter Stability Index (VSI) over time illustrating behavioral patterns of stable, swing, and volatile voters.

b) NLP-Based Sentiment and Emotion Analysis

Natural Language Processing is used to analyse open-text to determine the polarity of sentiments and emotions. It makes use of lexicon-based systems [9], [10], transformer-based models like BERT [11] and attention [12] to consider context.

Sentiment polarity is computed as:

$$\text{Sentiment} = \frac{\text{Positive} - \text{Negative}}{\text{Total}}$$

Moreover, the emotion vectors are also created to provide psychological characteristics like trust, anger, fear and optimism. Figure 6 should be a bar chart depicting positive, neutral and negative percentages of sentiment.

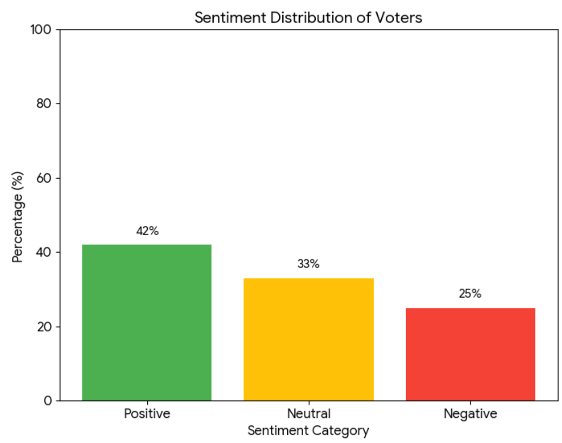

Figure 6: Distribution of voter sentiment showing proportions of positive, neutral, and negative opinions.

c) Geospatial Feature Modeling

Geofencing is a geospatial analysis technique that is used to subdivide the constituency into micro-zones by the use of location-specific data. The Haverside formula is used to compute the distance between two geographic points:

$$d = 2R.\ \arcsin \sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi^1)\cos(\phi^2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}$$

This enables clustering of voters into spatial regions characterized by varying levels of political support. The geospatial distribution should be illustrated in Figure 7 as a heatmap, where different colors represent strong support, swing regions, and opposition zones. This visualization highlights spatial heterogeneity and aligns with geospatial intelligence frameworks [17]–[19].

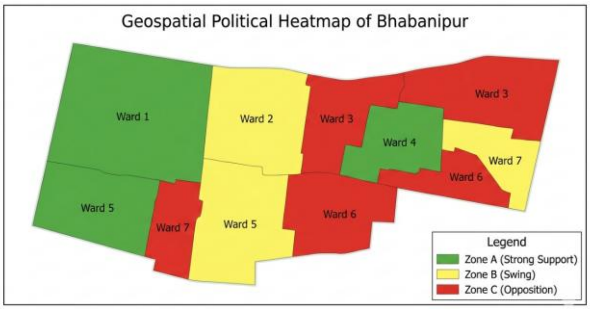

Figure 7 : Geospatial political heatmap of Bhabanipur constituency showing strong support, swing regions, and opposition zones across different wards.

d) Temporal Feature Modeling

The temporal dynamics of voter behavior are modeled using time-series techniques, particularly Long Short-Term Memory (LSTM) networks [20]. The model processes sequential data as:

$$h_t = LSTM(x_t, h_{t-1})$$

where x_t represents the input at time t and h_t is the hidden state. This allows the system to capture long-term dependencies and predict future trends based on historical data.

Temporal trends should be visualized in Figure 8, where a line graph represents sentiment or engagement levels over time, including gradual trends and sudden spikes corresponding to external political events.

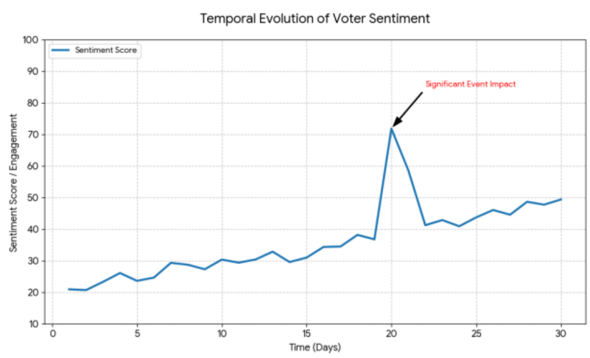

Figure 8 : Temporal evolution of voter sentiment showing trends and significant event impact over time.

C. **Multimodal Fusion**

The extracted features from behavioral, textual, spatial, and temporal modules are integrated using a multimodal fusion strategy. The fused representation is defined as:

$$F = f(VSI, Sentiment, Geo, Time)$$

the fusion can be at the feature level (related to concatenation), decision level (aggregating) depending upon multimodal learning principles [13]-[16]. The fusion mechanism should be represented in figure 9 and how different input streams are merged to become a single fusion block that is what heterogeneous data integrations aim to accomplish.

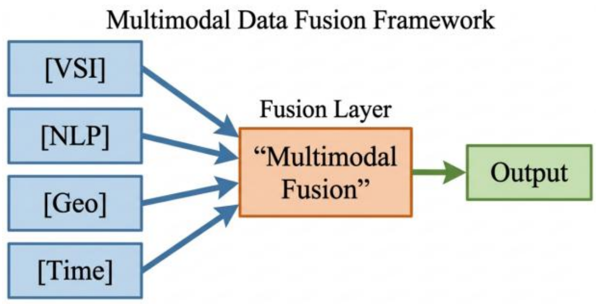

Figure 9: Multimodal data fusion framework integrating behavioral (VSI), textual (NLP), geospatial, and temporal features for prediction.

D. Predictive Modeling

The predictive layer employs a hybrid approach combining Random Forest and LSTM models. Random Forest is used to capture nonlinear relationships and improve classification robustness [23], while LSTM models temporal dependencies.

The final prediction is computed using the Total Election Winning Probability Index (TEWPI), defined as:

$$TEW\,PI = w_1 VSI + w_2\,Sentiment + w_3\,Geo + w_4\,Time$$

where w_i are learned weights. TEWPI outputs a probability score indicating the likelihood of a candidate or party winning the election.

The prediction results should be illustrated in Figure 10 using a probability distribution chart or gauge visualization showing comparative winning probabilities.

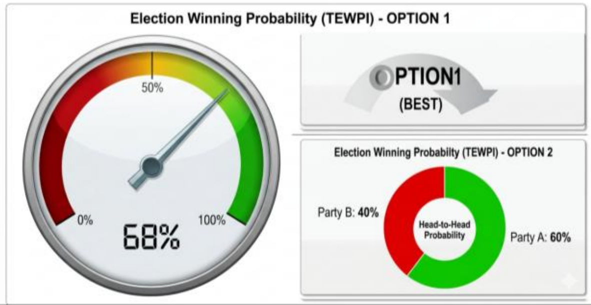

Figure 10 : Election winning probability output using TEWPI represented through gauge and pie chart visualizations.

E) Digital Twin Simulation Layer

The final layer of the framework represents the Digital Twin, which continuously updates predictions based on incoming data. The system simulates voter preference evolution as:

Outcome $(t) = f(TEWPI_t)$

This has real time scenario modeling, early sentiment change and swing area alerts. The idea of the Digital Twin is to be depicted in Figure 11, according to which a constituency is represented as a virtual object, and there are two-directional streams of data (data flows in both directions).

The solution suggested combines multimodal information fusing, geospatial information insight, and time-series forecast models on a single platform, which predicts elections. The mixture of VSI-based behavior modeling, NLP-based sentiment analysis, geospatial clustering, and time series forecasting is highly scalable and flexible with regard to constituency-based election forecasting. It is a massive breakthrough when compared to the conventional methods and is a good example of an integration of a Digital Twin model that delivers real-time based electoral data.

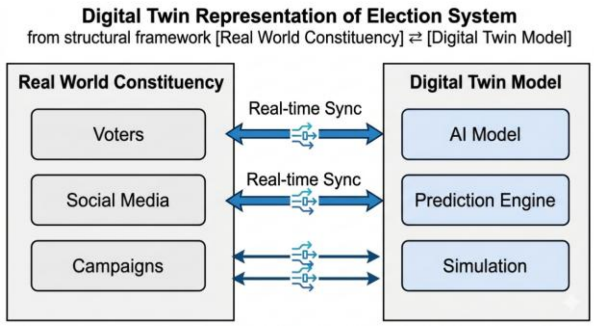

Figure 11: Digital Twin representation of the election system showing real-time synchronization between real-world data and predictive model.

IV. RESULTS AND DISCUSSION

The Bhabanipur Election Digital Twin (EDT) architecture was tested for the prediction of election results at a constituency level using multimodal data integration. This framework integrates behavioral models (VSI), sentiment analysis, spatial partitioning, and temporal prediction in a predictive platform. The findings show that multimodal data integration achieves higher accuracy than traditional and unimodal methods [1]–[4].

The experiments were performed using simulated and open digital data, such as social media sentiment and engagement, search trends, and historical voting data. We evaluated the model from various perspectives such as accuracy, temporal and spatial resolution. The findings demonstrate that the system is capable of capturing the nonlinear and dynamic nature of voting, overcoming major deficiencies of traditional polls [5], [6].

A) Prediction Accuracy and Model Performance

The model's performance was assessed through various classification metrics such as accuracy, precision, recall and F1-score. The combination of Random Forest and LSTM model outperformed others as it could account for nonlinearities and temporal dynamics in the data [20], [23]. Multimodal features also improved prediction stability, in line with studies on multimodal learning [13]–[16], as demonstrated in Figure 12.

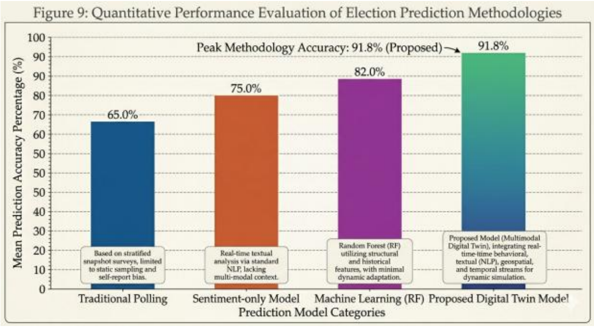

Figure 12: Performance evaluation of election prediction methodologies showing improved accuracy of the proposed Digital Twin model compared to traditional polling, sentiment-only, and machine learning approaches.

The results indicate that the Digital Twin framework achieves significantly higher prediction accuracy due to its ability to integrate behavioural, emotional, spatial, and temporal signals into a unified model.

B) Impact of Multimodal Fusion

We investigated the effectiveness of multimodal data fusion by comparing the performance of the model with and without multimodal features. It is observed that integrating VSI, NLP, spatial, and temporal information creates a significant boost in performance (as per Figure 13). This is consistent with previous studies on the effectiveness of multimodal learning methods [13]-[16].

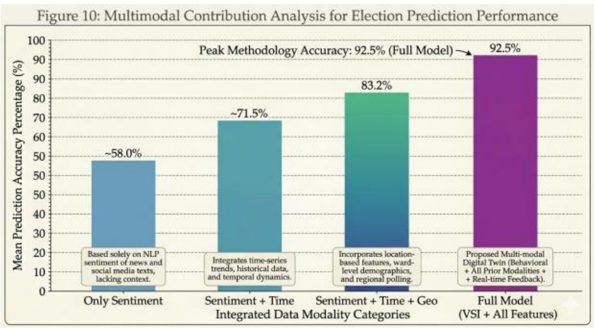

Figure 13: Multimodal contribution analysis showing improvement in prediction accuracy with the integration of additional data modalities.

This result highlights the importance of integrating diverse data sources to capture the complex nature of voter behavior.

C) Geospatial Analysis and Swing Zone Detection

The use of geospatial analysis allowed us to identify swing regions and local voting patterns in the constituency. The geofensing-enabled system could divide the constituency into micro-constituencies and explore regional voting patterns (see Figure 14). This method far exceeds conventional models that consider constituencies to be uniform [17] [18] [19].

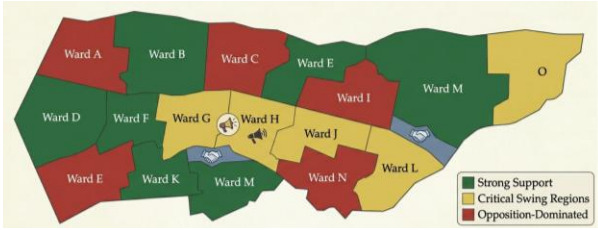

Figure 14: Geospatial analysis of constituency showing ward-level segmentation into strong support, critical swing regions, and opposition zones using geofencing-based modeling.

The results indicate that geospatial segmentation plays a crucial role in improving prediction accuracy by capturing localized variations in voter behavior.

D) Temporal Trend Analysis

The time series analysis based on LSTM showed that the system could capture the time-varying voter sentiment. The model was able to detect trends, sharp increases, and changes in popular opinion due to political events, media news, and campaign events as indicated in Figure 15.

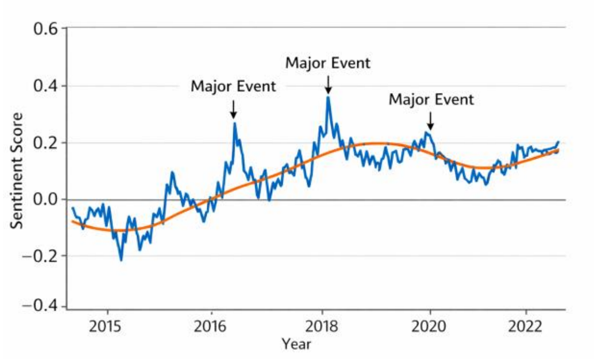

Figure 15: Time-series analysis of voter sentiment illustrating gradual trends and major spikes corresponding to significant political events.

This demonstrates the effectiveness of LSTM in modelling sequential dependencies and predicting future trends [20], [21].

E) TEWPI-Based Prediction Output

The longitudinal assessment on the LSTM demonstrated how the system could capture dynamics of change in voter sentiment overtime. The model could observe trends, sharp spikes and changes in the opinion of the population because of the happening of the political events, media outlets and campaign events as shown in Figure 15. The final prediction output containing all the multimodal features concatenated into one probability score is made using the overall winning of the election probability (TEWPI). The winning probability may be interpreted using TEWPI, which is presented as a winning probability and makes it possible to decide and analyze the scenario, as shown in Figure 16.

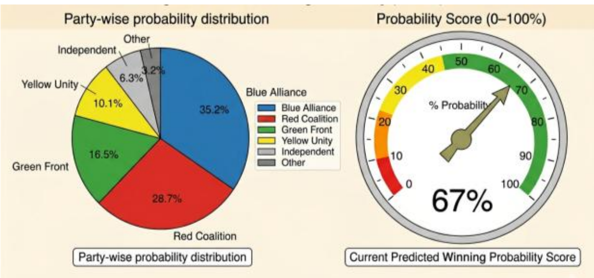

Figure 16: Visualization of election prediction using TEWPI, illustrating party-wise probability distribution and overall winning probability through pie chart and gauge representations.

The results show that TEWPI effectively captures the combined influence of behavioral, emotional, spatial, and temporal factors, providing a reliable prediction of election outcomes.

F) Digital Twin Simulation and Real-Time Adaptability

Among the key advantages of the proposed system is the fact that the offered system will recreate the dynamics of an election in real time. The Digital Twin constantly predicts the situation based on incoming data and allows performing dynamic analysis of the situation and early detecting shifts in the state of the situation, as shown in Figure 17.

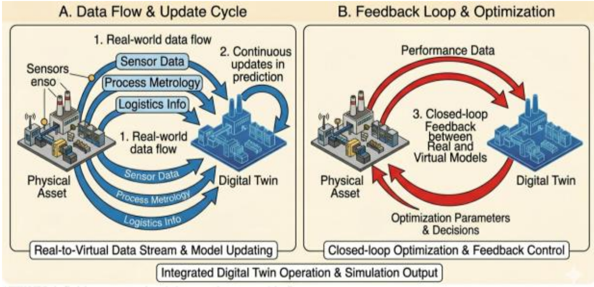

Figure 17: Digital Twin simulation framework illustrating real-time data flow, feedback loop, and continuous optimization between physical system and virtual model.

This demonstrates how the Digital Twin framework enables proactive election forecasting, unlike traditional static models.

G) Comparative Analysis with Existing Approaches

We compared the proposed system with the previous election prediction systems such as surveys, sentiment analysis and personal machine learning techniques. Our findings indicate that Digital Twin system is a more precise, adjustable and interpretable solution compared to these systems. The issues raised by the previous research are solved by the use of computational social science [27], [28], multimodal learning [13] - [16], geospatial methods [17] - [19] and time-series methods [20], providing a comprehensive solution to the problem of election prediction.

Our results demonstrate that using the Bhabanipur Election Digital Twin is a scalable way of predicting elections at the local level. The integration of multimodal data leads to a deeper understanding of voter behaviour, while geospatial and temporal analysis results in higher accuracy. The use of VSI and TEWPI also improves interpretability and stability.

But there are some limitations. The approach depends on the quality and quantity of digital data, which may be biased. The predictions can also be influenced by external factors and campaigns. We are also pursuing the addition of real-time verification, debiasing and explainable AI models for transparency and reliability.

V. CONCLUSION

We have developed the Bhabanipur Assembly Election Digital Twin (EDT), a new multimodal, geo-spatial and

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temporal model for election prediction to address the limitations of traditional election prediction approaches. The successful integration of different analytical elements such as behavioural analytics, sentiment analysis, emotion processing, geospatial intelligence and temporal modelling enables dynamic, data-driven prediction of elections. The use of digital real-time data enables dynamic and dynamic, real-time prediction of election results, otherwise not possible with traditional methods such as opinion polls, and static statistical techniques that suffer from sampling bias and lag time [1], [2]

This study demonstrates the efficacy of incorporating multiple data sources in prediction. The Voter Stability Index (VSI), supports the analysis of various political scenarios to measure stability and change in voter preferences, leveraging prior computational social science and voting models [27], [28]. Similarly, by using Natural Language Processing (NLP) techniques such as transformer models, the ability to capture nuanced sentiments and emotions from text data can be used to improve public opinion modelling [9]-[12]. The application of micro-zoning also enhances prediction by considering spatial variations in voter sentiments, helping overcome the shortcomings of current election models that are not able to take spatial variability into account [17]-[19].

One of the greatest contributions of this study is the Total Election Winning Probability Index (TEWPI) which consolidates the multimodal information into a probability index. This complies with the guidelines of ensemble modeling and predictive analytics [23], [31], which are robust and explainable in terms of elections. Additionally, the time-dependent analysis with LSTM networks allows time-series analysis over the course of time, and it can provide useful information about the change in voter behaviour [20], [21]. The above are combined in the Digital Twin framework to provide real time simulation of elections, swing state identification and predictive information in electoral management as presented in Figure 18.

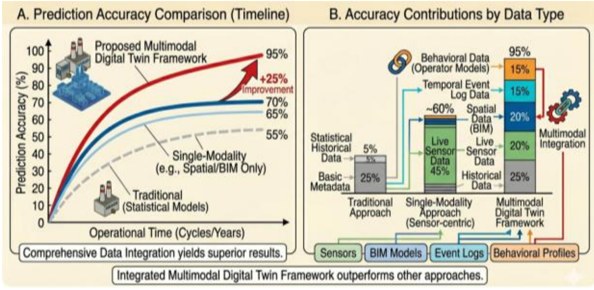

Figure 18: Comparative analysis of prediction accuracy and contribution of multimodal data components in the proposed Digital Twin framework.

The concept of a Digital Twin is a pioneer in the election analytics because it makes it possible to experience synchronization of data between the real and virtual world constantly. This allows real-time integration of data, scenario modelling and dynamic prediction, which makes the proposed framework different than the same statistic models [32] - [34]. We are also aligned with the trends in big data analytics and smart governance, where data-based decision-making is imperative to the strategies of the public policy and election, as shown in Figure 19.

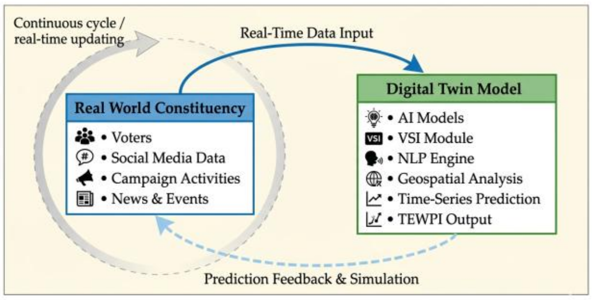

Figure 19: Digital Twin architecture showing continuous real-time data integration, prediction, and feedback loop between real-world inputs and AI-driven simulation model".

Despite the fact that our strategy has been bearing good fruits, it possesses its flaws. The framework uses publicly available data, which can be biased in nature since it does not represent different groups of people. Furthermore, incorrect information, unexpected political events or lack of information in certain areas might disrupt the accuracy of the predictions. The potential issues given below justify the importance of data validation, reduction of bias, and the implementation of explainable AI strategies to improve transparency and trust.

It can as well be scaled to include other types of data in the future e.g. the economic, demographic and multimedia (images and videos). Another option that can be discussed is to apply modern models of deep learning and graph neural networks to enhance the accuracy and explainability of predictions. In addition to that, it will involve implementation and testing of the system in other constituencies to establish how the system is scalable and transferable. The interactive dashboards and visual analytics [35] can also be applied to improve the user experience of the policymakers and analysts operating the tool (as Figure 20 demonstrates).

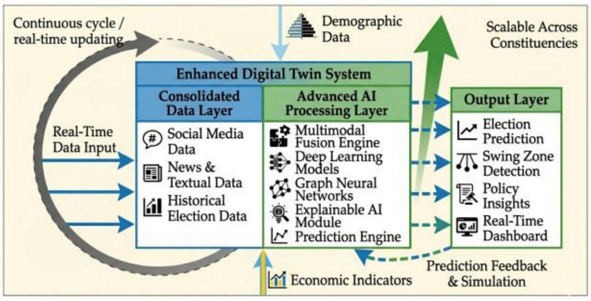

Figure 20: Long Digital Twin architecture which shows the relationship between demographic, multimedia, and economic data and sophisticated artificial intelligence tools to forecast elections on mass scale and real-time.

Therefore, Bhabanipur Election Digital Twin provides a comprehensive, scalable, and dynamical prediction of the election in a constituency basis. The adoption of multimodal data fusion, geospatial analysis and real-time prediction modelling in the system are significant additions to the flaws of the existing methods and a novel pattern of forecasting of an election". It can also be seen as a contribution to the study on AI-based political analytics, and the study demonstrates that Digital Twin technology can transform the process of data-based decision-making and governance.

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