TrumorGPT: Query Optimization and Semantic Reasoning over Networks for Automated Fact-Checking

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***Abstract*—In the age of social media, the rapid spread of misinformation and rumors has led to the emergence of infodemics, where false information poses a significant threat to society. To combat this issue, we introduce *TrumorGPT*, a novel generative artificial intelligence solution designed for automated fact-checking. TrumorGPT aims to distinguish "trumors", which are rumors that turn out to be true, providing a crucial tool in differentiating between mere speculation and verified facts. This framework merges machine learning with natural language processing techniques, leveraging a large language model (LLM) with few-shot learning for knowledge graph construction and semantic reasoning. TrumorGPT addresses the "hallucination" issue common in LLMs and the limitations of static training data by incorporating retrieval-augmented generation. This approach involves accessing and utilizing information from regularly updated knowledge graphs that consist of the latest news and information, ensuring that fact-checking of TrumorGPT is based on the most recent data. Accessing updated knowledge graphs greatly enhances the proficiency of TrumorGPT in delivering accurate and reliable information promptly. Evaluating with extensive datasets, TrumorGPT demonstrates superior performance in automated fact-checking. Its ability to effectively conduct automated fact-checking across various platforms marks a critical step forward in the fight against misinformation, enhancing trust and accuracy in the digital information age.**

***Index Terms*—Fact-checking, large language models, retrieval-augmented generation, semantic reasoning, knowledge graph.**

I. Introduction

In the recent digital environment, the rise of infodemics, characterized by the widespread and rapid dissemination of misinformation through social media, has emerged as a significant issue [7], [10], [23]. This problem becomes particularly acute during important events such as the United States presidential election, where misinformation can substantially influence public opinion and affect democratic processes. The 2020 United States presidential election serves as a prime example, overwhelmed with misinformation ranging from misleading narratives about candidates to unfounded claims about the electoral process. This surge in false information not only complicates public understanding but also threatens the integrity of democratic institutions. There is an urgent need for reliable fact-checking, especially during critical events like presidential elections. The ability to quickly and accurately distinguish truth from falsehood is essential in maintaining well-informed public discourse and upholding democratic principles. As misinformation becomes more complex and widespread, the development of advanced automated fact-checking tools becomes ever more necessary. These tools are crucial not only in counteracting the impact of infodemics but also in preserving factual accuracy in an era where the rapid speed and sheer volume of information pose unique challenges to traditional fact-verification methods.

Fact-checking is the process of verifying information to determine its accuracy and truthfulness [26]. Traditionally, this task has been manually performed by journalists and researchers who cross-reference claims with credible sources. However, the sheer volume and speed of information generated in the digital age have made manual fact-checking increasingly challenging [1]. In response to these challenges, advancements in large language models (LLMs) [4], [19], [20], [24] and the development of knowledge graphs have emerged as important solutions in automating the fact-checking process. LLMs, trained on extensive datasets, excel in understanding and generating text, making them adept at parsing and assessing the veracity of statements. Meanwhile, knowledge graphs provide a structured representation of relationships between entities and facts, offering a rich database for cross-referencing claims. However, LLMs can produce information that is coherent but factually incorrect. This issue often stems from the dependence of models on their training data, which may not always be up-to-date or fully comprehensive. Knowledge graphs, while invaluable in providing structured factual data, face challenges in coverage and timeliness. They may not encompass all domains of knowledge equally, potentially leading to gaps in available information for fact-checking.

In this paper, we present *TrumorGPT*, a novel generative artificial intelligence framework designed for automated fact-checking. TrumorGPT, aptly named, focuses on identifying "trumors", a term that blends "true" and "rumor" to describe rumors that ultimately prove to be factual. The concept of

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a trumor encapsulates instances where what initially appears as mere gossip or unfounded claims eventually aligns with reality. As such, TrumorGPT serves to uncover the truth from the rumors, effectively bridging the gap between skepticism and fact in public discourse. A unique aspect of TrumorGPT is its integration of a LLM with semantic knowledge graphs for fact verification through semantic reasoning. TrumorGPT employs two key technologies for verifying the truthfulness of news: TextRank [17] coupled with few-shot learning to enhance the construction of semantic knowledge graphs, and Generative Pre-trained Transformer 4 (GPT-4) [19] integrated with retrieval-augmented generation (RAG) [15] to provide up-to-date knowledge in semantic reasoning. The joint use of machine learning and natural language processing (NLP) techniques in TrumorGPT offers a comprehensive approach to automated fact-checking, making it a powerful tool in the fight against misinformation. Therefore, TrumorGPT provides a promising solution for fact-checking, effectively countering the spread of false information.

Overall, the contributions of the paper are as follows:

- We propose TrumorGPT, a novel framework that jointly integrates machine learning and NLP techniques, leveraging a LLM with semantic knowledge graphs and RAG for automated fact-checking.
- We enhance the construction of semantic knowledge graphs to improve semantic analysis and utilize RAG to provide updated knowledge, optimizing the performance of the LLM.
- We demonstrate the superior performance of TrumorGPT by conducting extensive evaluations on the verification of news truthfulness.

This paper is organized as follows. In Section II, we review the related work in studies of automated fact-checking. In Section III, we introduce TrumorGPT, which employs a LLM with knowledge graphs and RAG to verify facts through semantic reasoning. In Section IV, we demonstrate the performance evaluation results. We conclude the paper in Section V.

II. Related Work

Traditional fact-checking, carried out by expert journalists and analysts, finds it challenging to keep up with the overwhelming amount of information constantly produced in the digital world. Automated fact-checking, integrating NLP and machine learning, becomes particularly important for accurately verifying claims in the modern rapid information flow [9]. For instance, the authors in [13] propose a fully-automatic fact-checking framework utilizing a deep neural network with LSTM text encoding, which leverages the web as a knowledge source and combines semantic kernels with task-specific embeddings, for rumor detection and fact verification within community question answering forums. The work in [27] introduces a fact-checking framework for machine learning, using visualization of training data influence and physiological signals to measure and enhance user trust in predictive models. FactChecker in [18] applies a language-aware truth-finding approach, utilizing linguistic analysis to evaluate source objectivity and trustworthiness, and combines these factors with co-mention influence for a more accurate believability assessment of facts. Using deep learning, the authors in [11] develop a neural network model specifically for identifying Arabic fake news, leveraging convolutional neural networks and a balanced Arabic corpus to enhance the accuracy of fact-checking.

Knowledge graphs play a critical role in automated fact-checking, providing a structured and interconnected database of facts that significantly enhances the accuracy and efficiency of verifying information. In [5], the authors show computational fact-checking through knowledge graphs can efficiently validate information, effectively differentiating true from false claims using Wikipedia data. Tracy in [8] enhances knowledge graph curation by providing clear explanations for fact verification through rule-based semantic traces and a user-friendly interface. The work in [22] introduces a link-prediction model in knowledge graphs for computational fact-checking, which successfully assesses the truthfulness of various claims using large-scale graphs from Wikipedia and SemMedDB. FACE-KEG in [25] enhances explainable fact-checking by constructing and utilizing knowledge graphs to evaluate the veracity of claims and generate understandable explanations. Other works [6], [12], [14], [16], [21] utilize knowledge graphs for fake news detection, employing innovative models and methods to improve accuracy in fact-checking across various contexts.

III. TrumorGPT with Retrieval-Augmented Generation

In this section, we introduce TrumorGPT, a framework that utilizes a pretrained LLM for automated fact-checking. The process initiates with query processing, where input from users undergoes semantic similarity analysis to find relevant information. TrumorGPT employs few-shot learning, using the TextRank algorithm and examples to prepare the LLM for the creation of semantic knowledge graphs. These graphs incorporate information from the latest and updated knowledge base, facilitating the capability of the pretrained LLM for retrieval-augmented generation (RAG). The framework retrieves and synthesizes information, enriching the semantic knowledge graph, which is then used to apply semantic reasoning to the fact-checking task. The final output is a semantically reasoned answer that determines the factual accuracy of the input query. Fig. 1 provides a high-level overview of TrumorGPT.

A. Semantic Knowledge Graph

A semantic knowledge graph is an effective mechanism for encapsulating knowledge in a format that is both structured and interpretable by machines. This graph consists of vertices that symbolize entities and edges that represent the connections between them. The “semantic” aspect of the graph ensures that entities and their interrelations are based on meaningful, contextually relevant concepts, making them understandable to both machines and humans.

We represent a semantic knowledge graph as a directed graph $G = \{E, R, F\}$, where E denotes the set of entities, R

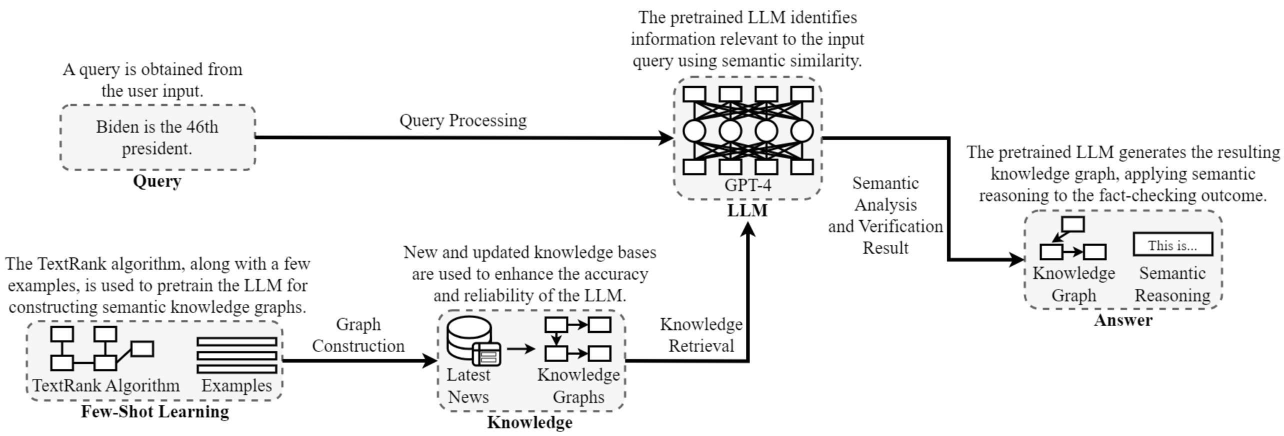

Fig. 1. The architecture of TrumorGPT, showcasing the workflow from user input to fact verification. TrumorGPT leverages advanced algorithms and an extensive knowledge base to generate a verified semantic knowledge graph and provide a reasoned answer for automated fact-checking.

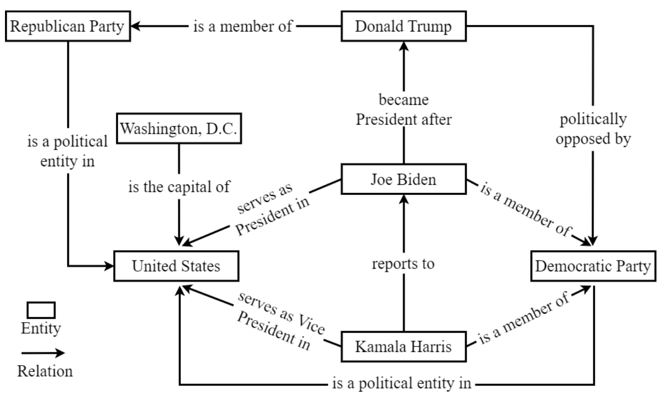

Fig. 2. An illustrative semantic knowledge graph, highlighting key political figures and relationships in the United States.

indicates the set of relations, and F is the triple set of relational facts. Each fact is represented as a triple $(h, r, t) \in F$, where $h \in E$ is the head entity, $t \in E$ is the tail entity, and $r \in R$ is the relationship between h and t. For example, (“`Biden`”, “`is`”, “`46th president`”) represents the fact that Biden is the 46th president. In a semantic knowledge graph constructed from a set of statements extracted from a resource like Wikipedia, factual relations among entities in those statements are represented as a large-scale network. The truthfulness of a new statement is evaluated based on its presence as an edge in this graph or the existence of a short path in the graph linking its subject to its object. Otherwise, the absence of such edges or short paths usually indicates that the statement is untrue. As a result, the task of fact-checking involves verifying if a query, represented as a triple (h, r, t), is true within the knowledge graph framework. In Fig. 2, we present a semantic knowledge graph illustrating the relationships between major political figures and entities in the political framework of the United States.

Creating a knowledge graph can be challenging due to the vast amount of information available, particularly when the user input is as extensive as an article. The key lies in identifying the central topics or the main ideas from the abundant data. This process of extracting key information enables the creation of a semantic knowledge graph that accurately represents the core themes and relevant connections within the larger text, ensuring that the most significant information is used for further semantic analysis and inference. To achieve this, we can leverage TextRank [17] for optimizing the knowledge graph. It functions similarly to the PageRank algorithm [3], focusing specifically on text processing. TextRank constructs a graph where vertices represent text units like sentences or keywords, and edges indicate the relationships based on co-occurrence within a certain window of words. Using graph-based ranking, each vertex is assigned a score:

$$S(V_i) = (1 - d) + d * \sum_{V_j \in \mathrm{In}(V_i)} \frac{w_{ji}}{\sum_{V_k \in \mathrm{Out}(V_j)} w_{jk}} S(V_j),$$

where $S(V_i)$ is the score for vertex V_i, d is the damping factor usually set to around 0.85, $\mathrm{In}(V_i)$ denotes vertices pointing to V_i, $\mathrm{Out}(V_j)$ denotes the vertices to which V_j points, and w_{ji} is the weight of the edge from V_j to V_i. The TextRank algorithm runs iteratively to calculate these scores until they stabilize, establishing the importance of each text unit.

B. Large Language Model with Retrieval-Augmented Generation

LLMs have become a fundamental part of NLP, offering impressive performance in tasks like text generation, sentiment analysis, translation, and question-answering. Trained on extensive datasets, these models use deep learning architectures to effectively process and interpret various aspects of language, making them highly useful in diverse NLP applications. In the context of knowledge graphs, LLMs can understand and analyze substantial amounts of text to identify relevant connections and information necessary for creating detailed and accurate knowledge graphs. In TrumorGPT, we particularly use Generative Pre-trained Transformer 4 (GPT-4) [19] to facilitate the automated fact-checking process.

GPT-4 serves as the foundation for conducting semantic similarity analysis in TrumorGPT, which compares user queries against a large corpus of text to identify relevant information. This process is critical for ensuring that the semantic knowledge graph reflects the content of the user query accurately. Through the few-shot learning approach with the TextRank algorithm, GPT-4 enables TrumorGPT to identify and extract key phrases and sentences. These elements highlight the central ideas within the text, serving as the building blocks for the semantic knowledge graph. By organizing these elements into a graph structure, TrumorGPT can represent the relationships and hierarchies among the various pieces of information. Few-shot learning with TextRank is particularly necessary when dealing with user inputs that are extensive, such as full-length articles rather than single-sentence queries. This approach allows TrumorGPT to quickly understand and adapt to the task of knowledge graph construction by learning from a small, representative set of examples. These examples train the framework to identify the core ideas from articles, which is an important skill when the input is lengthy and complex. By optimizing the learning curve of the GPT-4, TrumorGPT can efficiently generalize the process of knowledge graph construction to new and diverse inputs, eliminating the need for exhaustive retraining on large datasets while ensuring the knowledge graph remains focused and relevant, even when derived from extensive sources of text.

The "hallucination" issue in GPT-4 refers to instances where the model generates responses that are factually incorrect or not grounded in reality, often due to its dependence on static training data that may not be up-to-date or comprehensive. To mitigate this problem in TrumorGPT, RAG can be employed as a solution. RAG allows GPT-4 to access an updated knowledge base that includes the latest news and information, all organized in the form of structured knowledge graphs. In particular, TrumorGPT can be technically enhanced by RAG through the following tasks:

- Query processing and retrieval: Upon receiving a user query, TrumorGPT first processes it to understand the context and intent. With RAG, the framework then searches the knowledge base, composed of knowledge graphs that encapsulate the most recent knowledge in a structured format, to find information related to the query.
- Reference and verification: If the knowledge base contains graphs that directly correspond to the input query, TrumorGPT leverages this information to verify the truthfulness of the query. This process of direct verification depends on how relevant and recent the knowledge graphs are in relation to the query.
- Knowledge graph expansion: In situations where the knowledge base lacks a specific knowledge graph for direct verification, TrumorGPT enhances the existing graph related to the input query by adding new vertices and edges, integrating additional information and context. This expansion broadens the scope of the knowledge graph for a more comprehensive fact-checking process.
- Guidance for decision making: If there is not enough information for exact fact-checking, TrumorGPT provides additional, relevant knowledge from the knowledge base. This information acts as a guide for users, helping them make decisions regarding the veracity of their query.

RAG effectively equips GPT-4 with the ability to reference the most current and relevant data, going beyond its pretrained static dataset. This dynamic interaction with an evolving knowledge base significantly reduces instances of factual inaccuracies in the responses generated by GPT-4, making TrumorGPT a more reliable and up-to-date fact-checking tool.

IV. Performance Evaluation

In this section, we examine the effectiveness of our TrumorGPT framework in validating the truthfulness of news content as an application of fact-checking.

A. Data Collection

We enhance TrumorGPT with up-to-date knowledge by incorporating Resource Description Framework (RDF) triples from the latest-core collection of DBpedia [2], which automatically extracts structured data from Wikipedia reflecting the most recent updates. Focusing on the DBpedia Ontology dataset of triples, we construct a knowledge base with information exclusively in English. Given that the existing pretraining of GPT-4 includes knowledge up to April 2023, we concentrate on training it with data postdating this period to ensure knowledge of TrumorGPT remains updated. To address the limitations of GPT-4 in processing extensive external data, we selectively train it on triples related to United States politics, ensuring relevance and efficiency of the framework in a domain where accuracy is particularly consequential due to its impact on public discourse and policy.

B. Evaluation Approach

As the 2024 United States presidential election approaches, our focus in this study is on political news, recognizing the critical role of fact-checking in ensuring informed voter decisions and maintaining the integrity of the electoral process. Fact-checking is important before an election as it helps to clarify the positions and claims of candidates, contributing to a more transparent and fair political discourse. In this regard, we focus on PolitiFact, a well-known fact-checking organization that evaluates the accuracy of claims made by politicians, candidates, and others involved in United States politics. PolitiFact conducts fact-checking by researching statements and rating their accuracy, targeting a wide range of political statements from policy debates to campaign assertions. Due to its comprehensive and methodical approach to evaluating political statements, we consider the fact-checking outcomes by PolitiFact as our gold standard for assessing the performance of TrumorGPT. The well-established framework of PolitiFact provides a robust benchmark for comparing and validating the fact-checking capabilities of TrumorGPT in the area of political news, especially in the context of the upcoming United States presidential election.

PolitiFact employs a six-category rating system to evaluate the accuracy of statements: "True" for statements that are completely accurate with no significant omissions, "Mostly True" for statements that are accurate but require additional information or clarification, "Half True" for partially accurate statements that omit important details or take things out of context, "Mostly False" for statements containing some truth but lacking critical facts, "False" for completely inaccurate statements, and "Pants on Fire" for not only false but also ridiculous claims. GPT-4, as a language model, may struggle with the fine distinctions between these categories. Therefore, we simplify these into a binary system of "True" or "False" for practicality. We categorize "True", "Mostly True", and "Half True" as "True", indicating a tendency towards accuracy, and "Mostly False", "False", and "Pants on Fire" as "False", denoting significant inaccuracy or outright falsehood. This binary classification method simplifies fact-checking into just true or false categories, which is important for ensuring both accuracy and speed in the verification of information.

C. Verification of News Truthfulness

We evaluate TrumorGPT with a set of 100 statements from the "2024 Elections" category on PolitiFact, balanced with 50 true and 50 false claims. Fig. 3 displays the normalized confusion matrix, illustrating the fact-checking performance of TrumorGPT. We observe that the model correctly identifies 88% of true statements (true positives) and 93% of false statements (true negatives), demonstrating its proficiency in automated fact-checking. Meanwhile, TrumorGPT achieves a slightly better performance in identifying false statements over true ones. One possible explanation for this could be the nature of the data or the way misinformation is structured. False statements often present specific, identifiable inaccuracies or exaggerations, which the model can detect using the knowledge graph. In contrast, verifying the truthfulness of a statement often requires a comprehensive understanding and cross-referencing of facts, which can be more challenging and may lead to a marginally lower true positive rate. This phenomenon reflects a common pattern in fact-checking, where disproving a statement is often more feasible than definitively proving its accuracy, given the more straightforward nature of evidence required to refute a falsehood as opposed to the extensive and sometimes ambiguous evidence needed to confirm the truth. Table I presents two illustrative examples of TrumorGPT applied to fact-checking, detailing the complete outcomes, including the final semantic knowledge graphs and the corresponding semantic reasoning generated by TrumorGPT.

In addition to its impressive performance in the verification of news truthfulness, TrumorGPT also excels in validating factual statements, a capability that is greatly enhanced by the integration of the GPT-4 model. The advanced language comprehension and analysis capabilities of GPT-4 boost the accuracy and reliability of TrumorGPT in fact-checking. This enables TrumorGPT to effectively and accurately recognize the truth in various factual statements, making it a valuable tool in automated fact verification.

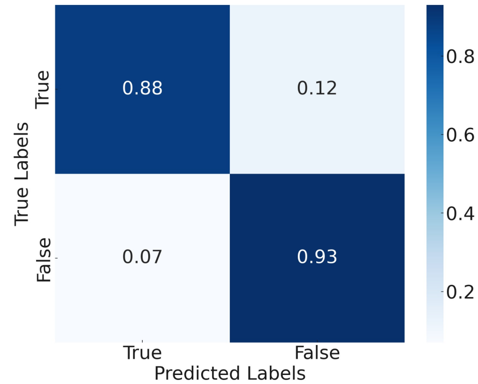

Fig. 3. A normalized confusion matrix for visualizing the performance of TrumorGPT in fact-checking.

V. Conclusion

Our proposed framework, TrumorGPT, leverages a large language model for accurate verification of statements in automated fact-checking. Effectively combining semantic knowledge graphs with retrieval-augmented generation, TrumorGPT exhibits robust performance in fact-checking, especially relevant to the political landscape of the United States in preparation for the 2024 presidential election. In particular, we demonstrate how TextRank, enhanced with few-shot learning, optimizes the formation of semantic knowledge graphs while retrieval-augmented generation refines the GPT-4 model with the most recent and updated information, addressing the "hallucination" issue in large language models. For future work, an interesting direction involves expanding the capabilities of TrumorGPT to tackle additional fact-checking tasks like identifying the origins of rumors or detecting spam content.

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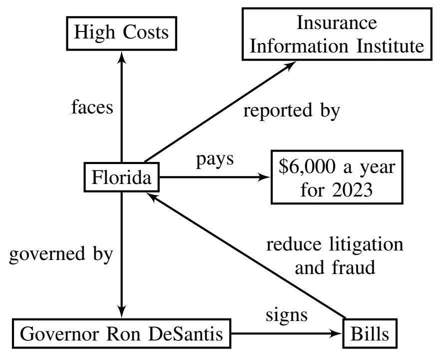
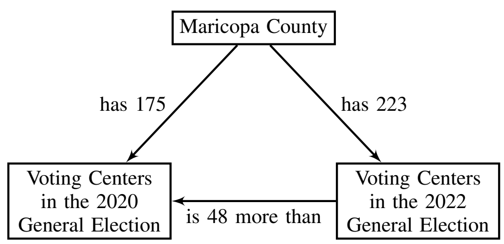
TABLE I

EXAMPLES OF FACT-CHECKING ACCURACY OF TRUMORGPT, ILLUSTRATING TWO DISTINCT CASES WHERE TRUMORGPT SUCCESSFULLY VERIFIES QUERIES RELATED TO UNITED STATES POLITICS.

Query	Semantic Knowledge Graph	Semantic Reasoning	Ground Truth
Florida has the highest homeowners insurance in the nation.		`The claim that Florida has the highest home insurance rates in the United States is true, primarily due to the state's high average premium of $6,000 as reported by the Insurance Information Institute for 2023. Contributing factors include efforts by Governor Ron DeSantis to address litigation and fraud, which are major drivers of these high rates, and the acknowledgement by industry experts that, although new laws might eventually lower premiums, the state's vulnerability to hurricanes means that insurance costs will remain high for the foreseeable future.`	True
Maricopa County intentionally reduced the polling places.		`The claim that Maricopa County intentionally reduced polling places is categorically false. Contrary to the assertion, the county actually increased its voting centers from 175 in 2020 to 223 in 2022, a 27% rise, primarily to accommodate more voters and reduce wait times. The issues faced on Election Day were due to technical glitches unrelated to the number of polling places. This evidence directly contradicts the claim of a reduction in polling places, making it a clear falsehood.`	False

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