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Posted Date: 31 October 2023

doi: 10.20944/preprints202310.1998.v1

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Marburg Virus Outbreak and a New Conspiracy Theory: Findings from a Comprehensive Analysis of Web Behavior

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Abstract: During virus outbreaks in the recent past web behavior mining, modeling, and analysis have served as means to examine, explore, interpret, assess, and forecast the worldwide perception, readiness, reactions, and response linked to these virus outbreaks. The recent outbreak of the Marburg Virus disease (MVD), the high fatality rate of MVD, and the conspiracy theory linking the FEMA alert signal in the United States on October 4, 2023, with MVD and a zombie outbreak, resulted in a diverse range of reactions in the general public which has transpired in a surge in web behavior in this context. This resulted in "Marburg Virus" featuring in the list of the top trending topics on Twitter on October 3, 2023, and "Emergency Alert System" and "Zombie" featuring in the list of top trending topics on Twitter on October 4, 2023. No prior work in this field has mined and analyzed the emerging trends in web behavior in this context. The work presented in this paper aims to address this research gap and makes multiple scientific contributions to this field. First, it presents the results of performing time series forecasting of the search interests related to MVD emerging from 216 different regions on a global scale using ARIMA, LSTM, and Autocorrelation. The results of this analysis present the optimal model for forecasting web behavior related to MVD in each of these regions. Second, the correlation between search interests related to MVD and search interests related to zombies (in the context of this conspiracy theory) was investigated. The findings show that there were several regions where there was a statistically significant correlation between MVD-related searches and zombie-related searches (in the context of this conspiracy theory) on Google on October 4, 2023. Finally, the correlation between zombie-related searches (in the context of this conspiracy theory) in the United States and other regions was investigated. This analysis helped to identify those regions where this correlation was statistically significant.

Keywords: Marburg virus; big data; data mining; data analysis; google trends; web behavior; data science; conspiracy theory

1. Introduction

The 2023 outbreak of the Marburg Virus Disease (MVD) was officially declared by the Ministry of Health and Social Welfare of Equatorial Guinea on February 13, 2023. This declaration followed the reporting of suspected fatalities caused by viral hemorrhagic fever from January 7, 2023, to February 7, 2023, and a positive RT-PCR case for Marburg virus on February 12, 2023, at the Institut Pasteur de Dakar in Senegal [1]. Between February 13, 2023, and June 7, 2023, 17 confirmed cases and 23 suspected cases were documented in the continental area of Equatorial Guinea. A total of 12 individuals among the confirmed cases succumbed to the illness, while all of the likely cases were reported as fatalities. It is worth noting that the case-fatality ratio among the confirmed cases of this

MVD outbreak was 75% (omitting one confirmed case for which the outcome was not known). The most recently confirmed patient was released from a Marburg treatment center in the Bata area of Litoral province on April 26, 2023, after the administration of two successive negative PCR tests for MVD. The Ministry of Health of Equatorial Guinea officially declared the conclusion of the outbreak on June 8, 2023, after a period of 42 days including two successive incubation periods during which no new confirmed cases were recorded [2].

As a result of this outbreak and the high fatality rate of MVD [3], in the last few months people from all over the world have been spending a lot more time than ever before on social media platforms and the internet in general to seek, share, access, and disseminate information about MVD [4,5]. During virus outbreaks of the past such as COVID-19 [6,7], MPox [8,9], Ebola [10,11], H1N1 [12,13], and MERS [14,15], researchers from different disciplines such as Healthcare, Epidemiology, Big Data, Data Analysis, Data Science, and Computer Science have studied and analyzed the underlining web behavior as web behavior provides insights into the public health needs, interests, motives, concerns, perspectives, and opinions related to virus outbreaks. Furthermore, web behavior analysis related to a virus outbreak has also had several applications related to the real-time surveillance of outbreaks [16], prediction of cases [17], forecasting the behavior of different strains of a virus [18], timely preparation of public health policies [19], better preparedness of healthcare systems [20], and timely implementation of public health policies and guidelines [21]. In addition to this, during virus outbreaks of the recent past, for example, COVID-19, such paradigms of information-seeking and sharing behavior on the internet led to the development and dissemination of different conspiracy theories which led to a range of reactions, both positive and negative, in the general public [22]. An example of a conspiracy theory in the context of COVID-19 was related to the role of 5G towers in spreading of the COVID-19 [23]. In January 2020, this conspiracy theory started on social media and it soon gained unprecedented attention, leading to a surge in Google Searches related to 5G and COVID-19 around that time. Furthermore, the rapid dissemination of this conspiracy theory led to people burning 5G towers in different regions in the United Kingdom [24]. Researchers from different disciplines have also investigated such patterns of web behavior related to the conspiracy theories associated with virus outbreaks of the past [25–27]. The recent outbreak of MVD followed by a warning signal (for testing purposes) sent by the United States Federal Emergency Management Agency (FEMA) to every TV, radio, and cellphone in the U.S. on October 4, 2023, led to an unusual conspiracy theory involving the MVD and zombies. One post about this conspiracy theory on Twitter [28], viewed close to 11 million times at the time of writing of this paper, states – *"Turn off your cell phones on October 4th. The EBS is going to "test" the system using 5G. This will activate the Marburg virus in people who have been vaccinated. And sadly turn some of them into zombies"*. In the past, there have been examples where just one Tweet started a conspiracy theory [29]. Since the publication of this Tweet, there have been several other posts on Twitter associated with this conspiracy theory which reveal the views, opinions, reactions, responses, and concerns of the general public in this regard. This conspiracy theory created a buzz in the global population to the extent that "*Marburg Virus*" featured in the list of the top trending topics on Twitter on October 3, 2023 [30]. To add to this, "*Emergency Alert System*" and "*Zombie*" featured in the list of top trending topics on Twitter on October 4, 2023 [31]. As a result of the widespread nature of this conspiracy theory and the associated concern and public reactions, Jeremy Edwards (press secretary and deputy director of public affairs at FEMA) stated publicly – *"I received it on my phone and saw it on the TV. And I can confirm to you that I am not a zombie"*, soon after the broadcast of the FEMA emergency alert signal [32]. In view of this recent outbreak of MVD and the associated conspiracy theory that created a significant buzz on the internet, which included this conspiracy theory being amongst the trending topics on Twitter for 2 days – October 3, 2023, and October 4, 2023, modeling and analyzing the underlining patterns of web behavior of the general public in this context becomes highly crucial to investigate. This serves as the main motivation for this research work.

1.1. Marburg Virus: A Brief Overview

In August of 1967, thirty people in Marburg and Frankfurt, Germany, became mysteriously and dangerously ill. This was the first known outbreak of MVD [33]. The virus was traced to African green monkeys that had previously been imported from Uganda. Infection occurred when autopsies were performed on the monkeys for the purpose of collecting kidney cell samples [33]. When the Ebola virus (EBOV) emerged in Africa nearly ten years later, in 1976, the two viruses were classified together as Filoviridae [33,34]. MVD appeared sporadically between the years 1975 and 1985, but it did not result in deaths the way that EBOV did, leading people to believe that MVD was not as deadly [35]. Though MVD is not a prevailing threat in endemic locations, it poses a threat to tourists or travelers, especially as they might bring the virus to other countries; the risk of infection also exists in laboratory workers [36]. Because of its danger, transmissibility, and lack of vaccine, the World Health Organization (WHO) categorizes MARV as the Risk 4 Group (RG4). RG4 is the highest risk group and defines pathogens as a serious risk to individuals and communities [37]. The MVD infection manifests as a zoonotic disease, but the original or natural host of the virus is yet to be identified [38–40]. However, researchers speculate that bats could be vital to the transmission of the disease, or they may also be the original carriers of MVD [41]. In fact, MVD was isolated from Egyptian fruit bats after the initial outbreak [42–46]. Research works involving the Gabonese bat populations suggest that MVD is enzootic, and its transmissibility poses a risk of appearing in other countries [47,48]. Transmission between humans usually occurs through bodily fluids such as blood, saliva, and urine. Such interactions tend to happen when caring for a sick patient but can include the handling of an infected corpse [49].

The disease is observed over three phases: generalization, early organ, and late organ or convalescence [50]. During the generalization phase, the patient usually displays symptoms similar to the flu. During the second phase, which occurs between days five to thirteen of the illness, patients may display psychological symptoms. This may manifest as general confusion and irritability but could also be seen as worse symptoms, like swelling of the brain and delirium. The last stage of the disease is either late organ or convalescence depending on if the patient is able to recover. Should a patient enter the late organ stage, they may experience dementia, a coma, or convulsions. Death usually comes about by shock from multiorgan failure. The convalescence phase is marked by a slow recovery with symptoms like muscle pain, exhaustion, and peeling of the skin where the rash appeared [50]. Nearly 600 MVD cases have been reported since the first outbreak. These recent cases of Marburg disease have catalyzed the creation of MARVAC, a WHO-coordinated cooperative aimed at tackling the Marburg vaccine [51,52]. The vaccine has since been under development through the use of the MVD glycoprotein and animal testing [53]. Of approved vaccines, Ad26-MARV, developed using the Ad26 vector encoding of MVD, is set to be moved forward in development. It is currently available for emergency use alongside another Ad-based vaccine, ChAd3-MARV, which takes the Ad vector from a chimpanzee. Several vesicular stomatitis virus-based vaccines are scheduled to advance to clinical testing after manufacturing, namely VSV-N4CTI-MARV, VSV-MARV Musoke vector, and VSV-MARV Angola vector [53].

1.2 Concept of Conspiracy Theories

A conspiracy theory is an explanation for an event or occurrence that typically cites outgroups or authority powers as the perpetrators. Douglas et al. [54] proposed that people believe in conspiracy theories due to three key psychological motives: knowledge, existential, and social. Knowledge refers to certainty and the desire to create patterns or fill gaps in understanding. Existential motives include exerting control or safety in one's own situation, and knowledge allows people to have the certainty to feel safe. Lastly, social motives may be a person's desire to fit into a group, and following conspiracy theories may provide them with the agency to look good or feel desirable in social settings.

In addition to the core psychological motives, conspiracy theories can appeal to certain demographics [55,56]. People who are more likely to believe in conspiracy theories tend to include those with lower levels of education, lower levels of income, weak social networks, and low media literacy [57–60]. Males, unmarried people, and unemployed people are also seen to have a higher belief in conspiracy theories [59]. A final reason why people might believe in conspiracy theories could be attributed to politics. Politically motivated conspiracy theories give people of a particular party the reasoning needed to further a point, argument, or campaign, regardless of whether the content is true or not [55]. Conspiracy theories tend to have largely negative social and/or psychological impacts [61]. Research shows that people who participate in conspiracy theory dialogue are less likely to vote or participate in politics in general due to a lack of trust in the political system [62–64]. Conspiracy theories can also be associated with prejudiced views of certain groups of people. Research into conspiracy theories suggests that said conspiracy theories can portend anti-Semitic beliefs, discrimination against Jewish people, and sometimes even racism towards groups who are not a part of the conspiracy theory at all. Such sentiments contribute to and exacerbate division between groups of people [65–67].

One of the more significant impacts of conspiracy theories may be scientific skepticism. Climate change, for example, is commonly the target of many conspiracy theories, driving people away from caring about the core issue [68]. Those who might believe in climate change conspiracy theories may also believe in theories that surround scientific evidence, like GMOs or the forensics of the 9/11 attacks [69,70]. Scientific skepticism of this nature can extend to issues of human health as well. Belief in anti-science theories correlates to unsafe health choices, like being anti-vaccines (especially the COVID-19 vaccine), not using contraceptives, or alternative medicinal practices, or refusing professional help for physical or mental illnesses [71–77]. Conspiracy theories surrounding COVID-19 specifically contributed to an unwillingness to comply with COVID-19 regulations [78,79]. The insights into why people believe in conspiracy theories may play a role in how they are transmitted as well. People generally only believe in conspiracy theories after learning about them, and they may come across them in certain political spheres. Prior works in this field have found that political agendas could be furthered by conspiracy theories, making people who fall into particular political categories more inclined to share conspiracy theories [80–83]. Conspiracy theories may also be used to generate doubt in mainstream politics and media [84]. Research work in this field has shown that people commonly avoid sharing conspiracy theories out of fear of ostracization. However, the involvement in politics and feelings generated by it may be so strong that it negates this fear anyway. This may further indicate how conspiracy theorists find community among each other [85].

The remainder of the paper is presented as follows. A review of recent works in this field is presented in Section 2. Section 3 presents the detailed methodology that was followed for the investigation, interpretation, and analysis of the underlying web-behavior. The results are presented and discussed in Section 4, which is followed by the conclusion.

2. Literature Review

A review of recent works related to web behavior investigation, interpretation, and analysis during recent virus outbreaks is presented in this section. This section is divided into three parts. Section 2.1 presents a review of recent works related to time series forecasting in the context of recent virus outbreaks such as COVID-19 and MPox as time series forecasting approaches have been popular in the last few years for modeling web behavior. Section 2.2 presents a review of various conspiracy theories that were associated with virus outbreaks in the recent past. Section 2.3 presents an overview of healthcare research based on web behavior analysis from Google Trends as Google Trends is the most popular platform for web behavior analysis [86] and it was used for data collection in this research project.

2.1. Review of Recent Works related to Time Series Forecasting in the context of recent virus outbreaks such as COVID-19 and MPox

To predict the spread of COVID-19, Shahid et al. [87] used Auto Regressive Integrated Moving Average model (ARIMA), support vector regression (SVR), long short-term memory (LSTM), and bidirectional long-short term memory (Bi-LSTM). They found that Bi-LSTM outperformed the rest when trying to predict cases of COVID-19. In a similar study, Chandra et al. [88] found that different types of LSTM models could be used to predict COVID-19 with high levels of accuracy. They used

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LSTM, Bi-LSTM, and encoder-decoder LSTM (ED-LSTM) to predict cases. While ED-LSTM tended to underperform compared to LSTM and Bi-LSTM models, it performed at the highest accuracy with static-split training. Alabduldrazzaq et al. [89] also used ARIMA in their study. Their work used cases in Kuwait and resulted in a correlation coefficient of 0.996, indicating that ARIMA was a strong contender for the best prediction model. In a study performed in India, the authors used ARMIA to predict where COVID-19 infections might occur [90]. Using data from Johns Hopkins University, they were able to accurately predict COVID-19 cases. Katoch et al. [91] used ARIMA modeling to devise numbers for the COVID-19 outbreak during the time of January 30, 2020, to September 16, 2020, in India. A study done in Brazil found that ARIMA models successfully predicted cases in Recife, contributing to the prevention effort [92]. In Slovakia, a spatiotemporal analysis was used to analyze the spread of COVID-19 [93]. Spatial autocorrelation was used to view cases across Slovakian districts, and data was synthesized with Moran's global autocorrelation index and local index. A similar study was done in Lebanon. Spatial autocorrelation was used with certain parameters to analyze COVID-19 cases across Lebanese districts, and El Deeb [94] found that geographic bordering, resident population, density, distance between district centers, and poverty density correlated to disease clustering and spread.

The work of Iftikhar et al. [95] focused on forecasting new cases and death counts related to the MPV virus using a hybrid forecasting system that combined time series and stochastic models. Long et al. [96] worked on addressing the global health concern during the MPox outbreak, particularly in the United States, and utilized machine learning models for short-term forecasting. Among the models tested, NeuralProphet emerged as the most efficient, achieving a low RMSE and high accuracy in predicting future cases. The work of Wei et al. [97] addressed the increasing prevalence of MPox cases in non-endemic countries, particularly in North America and Europe since May 2022. The researchers employed various forecasting models, such as ARIMA, exponential smoothing, LSTM, and GM(1,1), to predict daily cumulative confirmed MPox cases in different regions.

Priyadarshini et al. [98] used linear regression, decision trees, random forests, elastic net regression, ANN, and CNN to assess the spread of the MPox virus across different countries. The results indicated that CNNs performed the best in modeling the virus's spread, while time-series analysis using ARIMA and SARIMA models provided valuable insights for risk assessment and preventive measures. Pathan et al. [99] used a deep learning-based LSTM model to analyze the gene mutation rate of the MPox virus. The work of Eid et al. [100] introduced a novel approach called BER-LSTM, which optimized LSTM deep networks using the Al-Biruni Earth Radius (BER) algorithm to predict MPox cases accurately. Patwary et al. [101] examined the global spread of MPox using concepts of GIS technology and spatial data analysis. Du et al. [102] examined online search activity related to the MPox outbreak in China. The findings showed that regions with higher economic levels, particularly Beijing and Shanghai, exhibited more interest in MPox.

To summarize, these works have used time series forecasting models such as ARIMA, Autocorrelation, and LSTM, to analyze web behavior, internet activity, and related information during virus outbreaks in the recent past. However, none of these works have focused on applying any such models related to the recent surge in web behavior related to the 2023 MVD outbreak.

2.2. Review of various Conspiracy Theories that were associated with Virus Outbreaks in the Recent Past

The COVID-19 pandemic was plagued by the proliferation of conspiracy theories and false information. These encompass claims suggesting that COVID-19 was a fabrication, insinuations that the virus was artificially engineered and released as a bioweapon, and accusations of governments capitalizing on the crisis for anti-democratic purposes [103]. In the early stages of the pandemic, social media stories even propagated the idea that 5G technology was responsible for the spread of the virus [104]. Some conspiracy theories contended that the pandemic served as a guise for the clandestine injection of microchip quantum-dot spy software into individuals for surveillance purposes, gaining substantial traction on social media platforms [105]. Furthermore, there were assertions that COVID-19 testing, especially the use of nasopharyngeal swabs, could harm the blood-brain barrier or even infect individuals with the virus [106]. The conspiracy theories related to face masks included claims

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that masks could facilitate viral transmission or lead to oxygen deprivation and carbon dioxide poisoning [107]. Furthermore, misinformation extended to unverified therapies and remedies, encompassing homeopathic arsenic-based products, colloidal silver solutions, the use of high-dose vitamins as preventive measures, and various herbal remedies [108,109].

In general, conspiracy theories have the potential to have a significant negative impact. For example, false claims connecting 5G technology to the pandemic triggered attacks on telecommunication masts and subjected engineers to verbal and physical abuse in multiple countries, including the UK [110]. The repercussions of misinformation during infectious disease crises draw historical parallels, such as the HIV/AIDS pandemic, where denial of the virus's existence and the promotion of untested alternative solutions led to substantial public health concerns and loss of lives [111–113]. The findings from recent works indicate that belief in COVID-19 conspiracy theories was inversely related to adherence to health-protective behaviors and trust in guidance from public health experts [114,115]. In a comprehensive study of 82 hoaxes related to the 2023 MPox outbreak and their spread on social media, researchers found that the sources behind these hoaxes were mostly unknown (73.17%), making it challenging to identify the primary disinformants. In the remaining instances (26.83%), sources included figures with public notoriety (18.29%), fictitious sources (6.1%), and impersonated identities (2.44%). The predominant format of these hoaxes was a combination of image and text (39%), followed by primarily text-based hoaxes (36.6%) [116]. In a separate study analyzing conspiracy theories related to the MPox outbreak on TikTok, 153 videos were identified and analyzed. The most prevalent theme (46.4% of videos) asserted that MPox was a deliberately orchestrated pandemic introduced for power, control, or financial gain. A second category (33.3% of videos) revolved around vaccines, with content alleging that MPox was an excuse to mandate vaccines worldwide. To add to this, approximately 17.6% of videos claimed that the WHO was involved in the MPox outbreak to gain more power and potentially override national laws [117].

To summarize, these works show that virus outbreaks in the recent past have been associated with several conspiracy theories which have been investigated and analyzed by researchers from different disciplines. However, none of those works studied the emergence of the new conspiracy theory involving the MVD and the emergency alert signal sent by FEMA in the United States on October 4, 2023.

2.3. Review of Applications of Google Trends in Healthcare

Google Trends data has been of interest to researchers for the mining and analysis of the underlying web behavior related to various emerging technologies [118,119], global affairs [120,121], humanitarian issues [122,123], societal problems [124,125], and needs of different diversity groups [126,127]. In the last decade and a half, the utilization, applications, and use cases of Google Trends to mine, monitor, interpret, and analyze web behavior during epidemics, pandemics, and virus outbreaks have attracted a significant amount of attention from researchers from different disciplines. Ginsberg et al. [128] used Google trends to track influenza-like illness (ILI) for early detection and rapid response. By analyzing the relative frequency of specific queries, the authors accurately estimated ILI activity in various U.S. regions. Kapitány-Fövény et al. [129] utilized Google Trends to forecast the incidence of Lyme disease in Germany. The study spanned from 2013 to 2018, with data on Lyme disease incidence obtained from the Robert Koch Institute and Google search volumes for "Borreliose" in Germany. The authors applied a SARIMA model to the Lyme disease incidence time series and incorporated Google Trends data as an external regressor. The results showed that Google Trends data correlated well with reported Lyme disease incidence. Verma et al. [130] used Google Trends to predict disease outbreaks in India. The research explored the correlation between Google Trends data for diseases like malaria, dengue fever, chikungunya, and enteric fever in 2016 in Haryana and Chandigarh and IDSP data. The results show a strong temporal correlation between Google Trends data and the IDSP data, suggesting that Google Trends could be used as an early warning tool for disease outbreaks. The work of Young et al. [131] involved using Google Trends to predict weekly state-level cases of syphilis in the United States. By analyzing web behavior related to keywords associated with syphilis, the study aimed to determine whether such data could serve as a supplementary tool for monitoring and predicting syphilis outbreaks. Another work by Young et al. [132] involved using Google trends to forecast new HIV diagnosis cases in the United States. The study collected Google Trends search volume data for HIV-related keywords and combined it with state-level HIV case reports from the CDC. They developed a predictive model using a negative binomial approach and the Least Absolute Shrinkage and Selection Operator (LASSO) method. Morsy et al. [133] used Google trends to predict the Zika virus in Brazil and Columbia. It aimed to determine whether the search volume for the term 'Zika' on Google Trends could serve as an early surveillance system for anticipating Zika outbreaks. The researchers used time-series forecasting models to establish a relationship between the weekly Zika cases and the corresponding Google search query data. As can be seen from this review, in these works Google Trends was used for the mining and analysis of relevant web behavior during virus outbreaks of the past such as Lyme disease, malaria, syphilis, HIV, ILI, and Zika virus. However, none of these works focused on the analysis of web behavior in the context of the 2023 MVD outbreak.

To summarize, time series forecasting, investigation of conspiracy theories, and web behavior mining and analysis using Google Trends during virus outbreaks have attracted the attention of researchers from different disciplines such as Healthcare, Epidemiology, Big Data, Data Analysis, Data Science, and Computer Science in the last few years. However, prior works in this field have multiple limitations as follows:

- The works that applied time series forecasting models on relevant web behavior did not investigate the web behavior data related to the 2023 MVD outbreak.
- Some of the works related to the applications of time series forecasting models to model web behavior during virus outbreaks did not focus on:
    - studying the web behavior from different geographic regions.
    - comparing the performance of different time series forecasting models to determine the optimal model for studying web behavior in different regions.
- Even though several works in this field have studied the development and dissemination of conspiracy theories related to virus outbreaks in the recent past such as COVID-19 and MPox, none of those works studied the relevant web behavior data in the context of the new conspiracy theory involving the Marburg Virus and the FEMA emergency alert signal.
- Relevant web behavior data from Google Trends has been mined and analyzed in several prior works in this field to understand and interpret multimodal components of web behavior during virus outbreaks. However, such works did not focus on mining, analyzing, or interpreting the web behavior related to new conspiracy theories involving the Marburg Virus and the FEMA emergency alert signal.

The work presented in this paper aims to address these research gaps. The step-by-step methodology that was followed is outlined in Section 3 and the results are presented and discussed in Section 4.

3. Methodology

This section is divided into two parts. In Section 3.1 an overview of the working of Google Trends and the procedure that was followed for data collection using Google Trends is presented. Section 3.2 presents the methodology that was followed for the development of the time series forecasting models and the models for correlation analysis, which were applied to the data collected from Google Trends.

3.1. Overview of the Data Collection Architecture and Description of Data Collection

The data analyzed in this research work was collected from Google Trends [134]. Google Trends is a web-based tool provided by Google that allows users to delve into and assess the search interest and prevalence of topics, keywords, or search queries over time. It equips individuals with the means to gauge how frequently specific terms are queried on Google from different geographic regions, offering valuable insights into the dynamic trends and curiosities of online users [135]. Furthermore, Google Trends provides geographic data, facilitating the identification of regions or counties where a topic garners the greatest attention. This tool also provides information regarding related queries, spotlighting frequently associated search terms with the chosen topic, and facilitating the exploration of interconnected trends and inquiries of interest to users. Google Trends also supports comparative analysis, allowing users to gauge the relative popularity of multiple search terms [136].

Google Trends offers three key benefits when compared to traditional surveys. First, it eliminates the cost associated with data collection and analysis, in contrast to conventional surveys, which often come with financial implications. Second, conducting routine surveys across a diverse global user base can be a formidable challenge, whereas Google Trends effortlessly taps into the worldwide search data generated daily on Google, simplifying the process of data collection and analysis. Third, Google Trends provides data that can be easily mined and analyzed, avoiding delays inherent in traditional surveys, which may be subject to time constraints related to participant recruitment and inclusion criteria [137,138]. There are two mathematical equations that underline the functioning of Google Trends, which are shown as Equation (1) and Equation (2). In these equations, "q" represents the number of searches for the query in the location "l" during the period "t". Here, Q(l, t) is the set of all the queries made from "l" during t, and $\pi(n(q,l,t)>\tau)$ is a dummy variable. The dummy variable serves as an indicator, taking the value 1 when the query meets the popularity threshold $n(q,l,t)>\tau$ and 0 otherwise. To add to this, Equation (1) yields Relative Popularity (RP) values that are subsequently scaled to fit within a range of 0 to 100, and Equation (2) provides the numerical value of the Google Trends Index (GTI).

$$RP(q,l\,,t) = \frac{n(q,l,t)}{\sum_{q\in Q(l,t)} n(q,l,t)} \times \pi_{(n(q,l,t)>\tau)} \tag{1}$$

$$GTI(q,l,t) = \frac{RP(q,l,t)}{max\{RP(q,l,t)_{t\in 1,2,\ldots,T}\}} \times 100 \tag{2}$$

Google Trends offers a range of features that provide valuable insights related to web behavior on Google. The "Explore" feature allows users to dig deeper into online interests, enabling the exploration of keyword popularity over chosen time periods and regions. Google Trends also provides "Trending Searches", offering both daily search trends and real-time search trends for a selected region. For those interested in historical trends, the "Year in Searches" feature lets users explore what was trending in a specific region during a particular year. Additionally, Google Trends offers "Subscriptions", allowing users to receive updates on specific topics or trending searches via email. These features collectively make Google Trends a powerful tool for the mining and analysis of web behavior on different topics with a specific focus on virus outbreaks.

For the work presented in this paper. Google Trends was used for collecting data regarding the 2023 MVD outbreak and the conspiracy theory linking the MVD outbreak, a zombie outbreak, and the FEMA emergency alert signal. The workflow diagram in Figure 1 shows the step-by-step procedure that was followed for data collection using Google Trends. At first, the search queries were set to compile MVD-related and zombie-related search interests, and the geolocation was set to worldwide. Thereafter, in the "Search Category" option on Google Trends, all categories option was selected and for the type of search data to be mined, "Web Search" was selected as the relevant web behavior data was being mined. After setting these specifications for the data mining process, an API call to Google Trends was performed for the weekly data between October 2, 2023, to October 9, 2023. There were primarily two reasons why the data mining was performed for this time range. First, the date when the FEMA emergency alert signal was broadcasted was October 4, 2023, and the search interest data on that day as well as around that day is relevant to investigate. Second, Google Trends provides several options for data mining. Although custom timelines can be provided to the Google Trends API. However, selecting the timeline as "Past 7 days" provides the hourly search interest data for each day in the 7-day period. In this work, the investigation also included the analysis of search interests related to this conspiracy theory right after the broadcasting of the FEMA emergency alert signal. So, obtaining the hourly search interest data was necessary. After this data collection was completed, the master dataset comprised the hourly search interests related to MVD and search interests related to zombies (in the context of MVD-related conspiracy theory) between October 2, 2023, to October 9, 2023, for 216 regions. As this data was collected using Google Trends, as per the Google Trends algorithm, the highest value of the search interest was 100 and the lowest value was 0. The names of these 216 regions are shown in Table 1. These regions recorded significant search interests related to MVD and this conspiracy theory, so the data of search interests from these regions was included in the development of the master dataset.

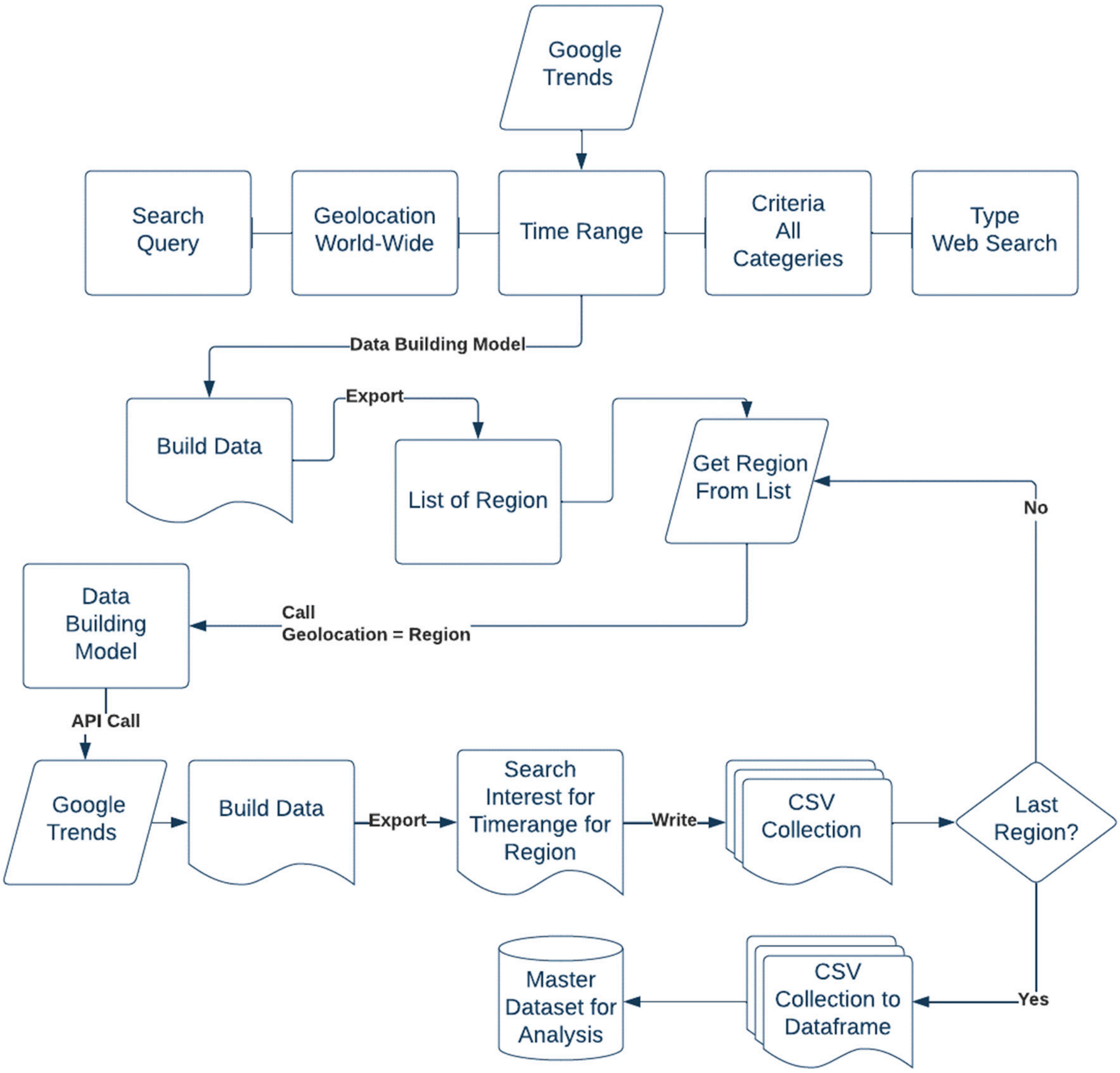

Figure 1. A workflow diagram to represent the data collection and the development of the master dataset using Google Trends.

Table 1. List of 216 regions for which data was collected using Google Trends.

List of Regions
Afghanistan, Åland Islands, Albania, Algeria, American Somoa, Andorra, Angola, Antigua & Barbuda, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia & Herzegovina, Botswana, Brazil, British Virgin Islands, Brunei, Bulgaria, Burkina, Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Cayman Islands, Chad, Chile, China, Colombia, Comoros, Congo – Brazzaville, Congo – Kinshasa, Costa Rica, Côte d'Ivoire, Croatia, Cuba, Curaçao, Cyrpus, Czechia, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Estonia, Eswatini, Ethiopia, Faroe Islands, Fiji, Finland, France, French, Guiana, French, Polynesia, Gabon, Gambia, Georgia, Germany, Ghana, Gibraltar, Greece, Greenland, Grenada, Guadeloupe, Guam, Guatemala, Guernsey, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong,

 doi:10.20944/preprints202310.1998.v1

Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Isle of Man, Israel, Italy, Jamaica, Japan, Jersey, Jordan, Kazakhstan, Kenya, Kosovo, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Macao, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Martinique, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar (Burma), Namibia, Nepal, Netherlands, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Northern Mariana Islands, Norway, Oman, Pakistan, Palestine, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Réunion, Romania, Russia, Rwanda, Samoa, San Marino, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Sint Maarten, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Korea, South Sudan, Spain, Sri Lanka, St. Barthélemy, St. Helena, St. Kitts & Nevis, St. Lucia, St. Martin, St. Pierre & Miquelon, St. Vincent & Grenadines, Sudan, Suriname, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad & Tobago, Tunisia, Türkiye, Turkmenistan, Turks & Caicos Islands, U.S. Virgin Islands, Uganda, Ukraine, United Arab Emirates, United Kingdom, Uruguay, USA, Uzbekistan, Vanuatu, Venezuela, Vietnam, Western Sahara, Yemen, Zambia, Zimbabwe

3.3. Methodology for performing Time Series Forecasting

The data collected using Google Trends (discussed in Section 3.2) comprised the search interests related to MVD recorded from relevant Google Searches from the 216 regions. As Google Searches serve as an indicator of the needs, interests, motives, concerns, perspectives, and opinions of the global population during a virus outbreak, several prior works in this field have developed time series forecasting models to accurately predict web behavior during virus outbreaks (reviewed in Section 2.1). As discussed in Section 2.1, such works did not focus on predicting web behavior related to the recent outbreak of MVD. To add to this, several works related to time series forecasting used only one specific model for time series forecasting out of some of the most popular models such as ARIMA, Autocorrelation, or Long Short-Term Memory network (LSTM). The work presented in this paper addresses both limitations. More specifically, programs were written in Python 3.11.5 to develop and implement all these models – ARIMA, Autocorrelation, and LSTM on the web searches related to MVD emerging from 216 regions (Table 1) and the performance characteristics of these models per region for all the 216 regions was computed. The pseudocodes of these programs are shown in Algorithms 1, 2, and 3, respectively.

Algorithm 1: ARIMA for Time Series Forecasting of Web Behavior related to MVD

```
Input: Master Dataset for Analysis
Output: ARIMA Forecast for the Data, Performance Metrics (RMSE, MSE, AE)
File Path
dataframe = load the data files
regions[] = region names
for each region in regions do:
    dataset = get values from dataframe: marburg virus: <region>
    dataset = convert dataset to float32
    x = dataset
    size = calculate size as 75% of all x
    split x into:
            train: from start to size
            test: from size to end x
    history = train value
    predictions_test = empty list
    for data in test do:
        model = history, order=(0,1,0)
        model_fit_test = fit model
        output_test = forecast by fitted model
        yhat_test = output[0]
        predictions_test ←— append(yhat)
        obs_test = test[data]
        history ←— append(obs)
    end for
    predictions_train = empty list
    for data in train do:
        model_train = ARIMA history, order(0,1,0)
```

```
        model_fit_train ⟵ fit model
        output_train ⟵ get forecast
        yhat_train ⟵ output_train[0]
        predictions_train ⟵ append(yhat_train)
        obs_train ⟵ train[data]
        history ⟵ append(obs_train)
    RMSE = calculate RMSE (test, prediction_test), calculate RMSE (train, prediction_train)
    MSE = calculate MSE (test, prediction_test), calculate MSE (train, prediction_train)
    AE = calculate AE (test, prediction_test), calculate AE (train, prediction_train)
    predictionsplot = empty list
    end for
    for data from 0 to dataset length do:
        if data <= predicitons length do:
                predictionsplot ⟵ append(np.nan)
         else:
                index = length of dataset – data
                predictionsplot ⟵ append_prediction(index)
    plot (dataset label = ground truth, predictions_train, predictions_test)
    show and save the plot
    end for
end for
```

Algorithm 2: Autocorrelation for Time Series Forecasting of Web Behavior related to MVD

```
Input: Master Dataset for Analysis
Output: Autocorrelation Forecast for the Data, Performance Metrics (RMSE, MSE, AE)
dataframe = load the data files
for each region in regions do:
    dataset = get values from dataframe: marburg virus: <region>
    dataset = convert dataset to float32
    x = dataset
    size = calculate size as 75% of all x
    split x into:
            train: from start to size
            test: from size to end x
    windows = 24
    model = Autoreg(train, lags= 24)
    model_fit = fit the model(training data)
    coef = coefficients from the model fit
    lag = last 24 values of the dataset
    prediction_test = empty list
    for each data in test do:
        length = history length
        lag = last window value in history
        yhat = coef [0]
        for each d in 0 to windows – 1 do:
                yhat_test+= coef[d+1] * lag[windows-d-1]
        obs_test = test [data]
        prediction_test ⟵ append(yhat_test)
        history ⟵ append(obs_test)
    end for
    prediction_train = empty list
    for data in train do:
        length = length of history
        lag = last window values from history
        yhat_train = coef[0]
     end for
     for each data in history do:
                yhat_train += coef[d + 1] * lag[window - d – 1]
     obs_train ⟵ train[data]
     prediction_train ⟵ append(yhat_train)
     history ⟵ append(obs_train)
     end for
    RMSE = calculate RMSE (test, prediction_test), calculate RMSE (train, prediction_train)
```

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```
    MSE = calculate MSE (test, prediction_test), calculate MSE (train, prediction_train)
    AE = calculate AE (test, prediction_test), calculate AE (train, prediction_train)
    for each t3 from 0 to the length of the series do:
        if t3 <= length of predictions2 then:
                predicionsplot ⟵ append(np.nan)
        else:
                index2 ⟵ length of dataset – data
                predictionsplot    append_prediction(index)
    plot (dataset label = ground truth, predictions_train, predictions_test)
    show and save the plot
    end for
end for
```

Algorithm 3: LSTM for Time Series Forecasting of Web Behavior related to MVD

```
Input: Master Dataset for Analysis
Output: Autocorrelation Forecast for the Data, Performance Metrics (RMSE, MSE, AE)
dataframe = load the data files
for each region in regions do:
    tf.keras.utils.set_random_seed(1)
    tf.config.experimental.enable_op_determinism()
    Function create_dataset(dataset, look_back=1):
            dataX = empty list
            dataY = empty list
            for i from 0 to (len(dataset)-look_back-1 do:
                a = dataset segment from i and size look_back
                dataX ⟵ append(a)
                dataY ⟵append(dataset[i+look_back, 0]
                np.array (dataX)
                np.array (dataY)
                return (data)
            end for
    end of Function
    dataset = get values from dataframe: marburg virus: <region>
     dataset = dataframe.values
     dataset = convert dataset (float32)
     scaler = MiniMaxScaler(feature_range=(0,1))
     dataset = fit, transform dataset
     train_size = 75% of all dataset
     test_size = len(dataset) – train_size
     look_back = 1
         trainX, trainY = create_dataset(train, look_back)
         testX, testY = create_dataset(test, look_back)
         trainX = reshape trainX with dimension
         testX = reshape testX with dimension
     model = Sequential()
     model.add(LSTM(100, input_shape=(1, look_back)))
     model.add(Dense(1))
     model.compile(loss='mean_squared_error', optimizer='adam')
     model.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)
     trainPredict = inverse transform by scaler
     trainY = inverse transform by scaler
     testPredict = inverse transform by scaler
     testY = inverse transform by scaler
     trainPredict = model.predict(trainX)
     testPredict = model.predict(testX)
        RMSE = calculate RMSE (test, testPredict), calculate RMSE (train, trainPredict)
        MSE = calculate MSE (test, testPredict), calculate MSE (train, trainPredict)
        AE = calculate AE (test, testPredict), calculate AE (train, trainPredict)
     testPredictPlot = np.empty_like(dataset)
     testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict
     trainPredictPlot = np.empty_like(dataset)
     trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict
    plot (dataset label = ground truth, trainPredictPlot, testPredictPlot)
```

```
    show and save the plot
end for
```

Figure 2 shows a flowchart that outlines the working of these models and how the same was applied to the master dataset. As can be seen from Figure 2 and Algorithms 1, 2, and 3, the performance of these models for time series forecasting was evaluated by computing the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) for both the train set and the test set. The results of the same are presented in Section 4.

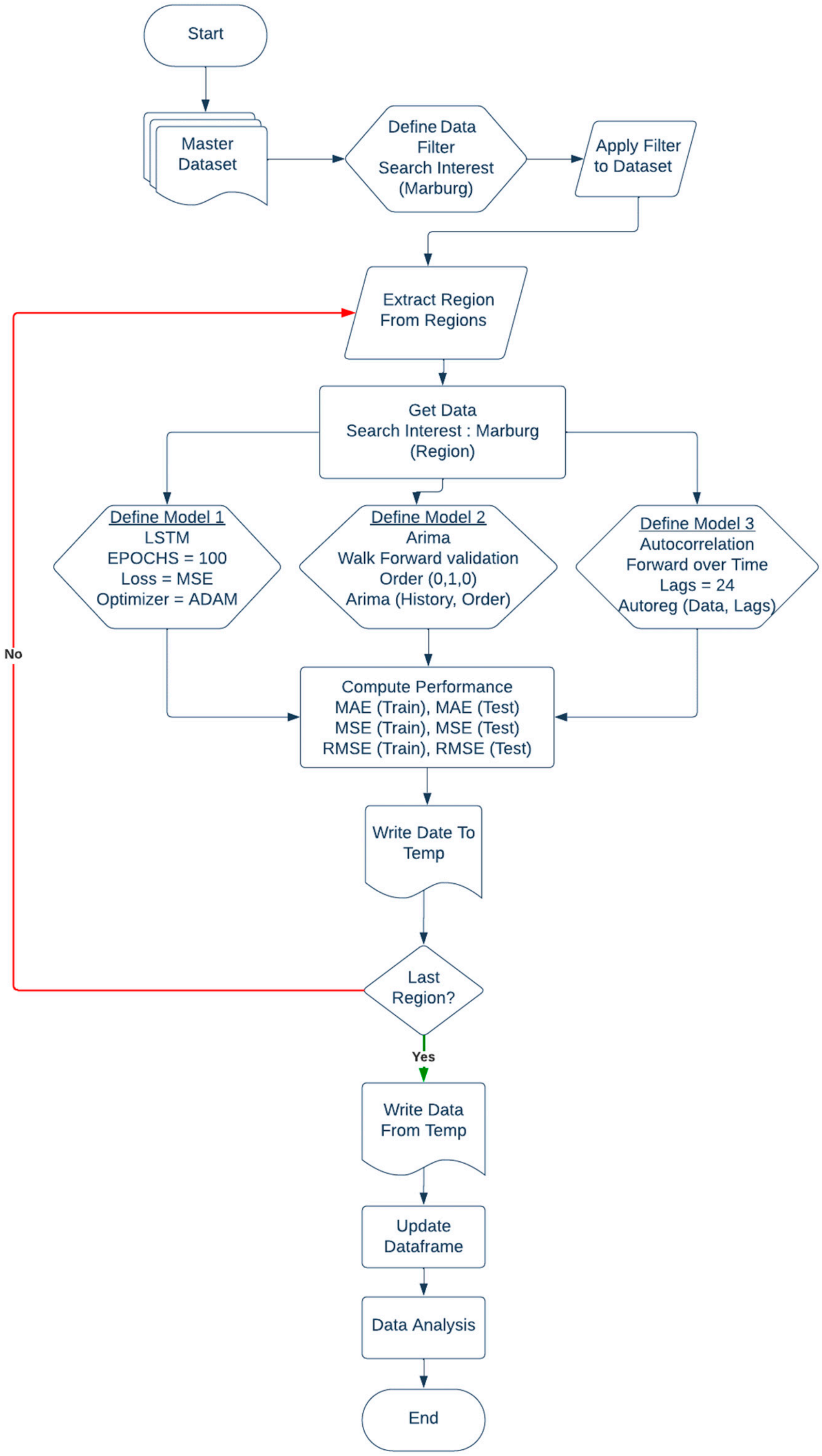

Figure 2. A flowchart to represent the application of Algorithm 1 (Model 1), Algorithm 2 (Model 2), and Algorithm 3 (Model 3) to the master dataset.

3.4. Methodology for Correlation Analysis

The section presents the specifics of the correlation analysis that was performed on the master dataset. The dataset contained search interests from relevant Google Searches related to MVD and the conspiracy theory for each region in the list of 216 regions. For each region, the correlations between these two types of search interests were investigated using Pearson's correlation. Thereafter, the nature of the correlation i.e., statistically significant, or not statistically significant was determined based on the p-value of the correlation. To add to this, the correlation between the search interest data related to this conspiracy theory in the United States and the remaining countries was also evaluated using Pearson's correlation to determine the nature of the correlation i.e., statistically significant, or not statistically significant. Figure 3 represents a flowchart that shows the step-by-step process that was performed in this regard to develop and apply the models for correlation analysis. Algorithm 4 represents the pseudocode of the program that was written in Python 3.11.5 to check for correlations between web behavior related to MVD and this conspiracy theory and to determine the nature of the same. Another program was also written to check for correlations between the web behavior related to this conspiracy theory in the United States and other countries. To avoid possible redundancy, the pseudocode of that program is not presented in this paper.

Algorithm 4: Correlation between MVD and Conspiracy Theory related Web Behavior

```
Input: Master Dataset for Analysis
Output: Pearson's r-value and p-value for each region
dataframe = load the data files
files = get the list of all CSV files in the master dataset using a recursive search
country = empty list
Name = empty list
for each file_name in files do:
      i ⟵ 0, col1 ⟵empty list, col2 ⟵empty list
      for each date in the first column of f do:
            if specific date exists then:
                  if second column of f at the ith row is an integer or is digit then:
                        col1⟵ append the integer value
                  else
                        col1⟵ append 0
                  if third column of f at the ith row is an integer or is digit then:
                        col2⟵ append the integer value
                  else
                        col2⟵ append 0
            end if
       increment i
end for
country ⟵append col, col2
r_value = empty list, p_value = empty list, significance = empty list
for each entry c in country do:
      stat_1 = calculate pearson correlation between c[0] and c[1]
      p_1 ⟵ extract second value from stat_1
      p_0 ⟵ extract first value from stat_1
      r_value ⟵ p_0, p_value ⟵ p_1
      if p_1 is less than 0.05 then:
            significance ⟵statically significant
      else:
            significance⟵ not significant
end for
open file in writing mode as CSV output:
         writer = CSV writer for CSV output
         write the header row with columns
          for i from 0 to length of country do:
               row⟵ empty list
               row [i] ⟵ append(name[i], r_value[i], p_value[i], significance[i])
               write row to the CSV
          end for
```

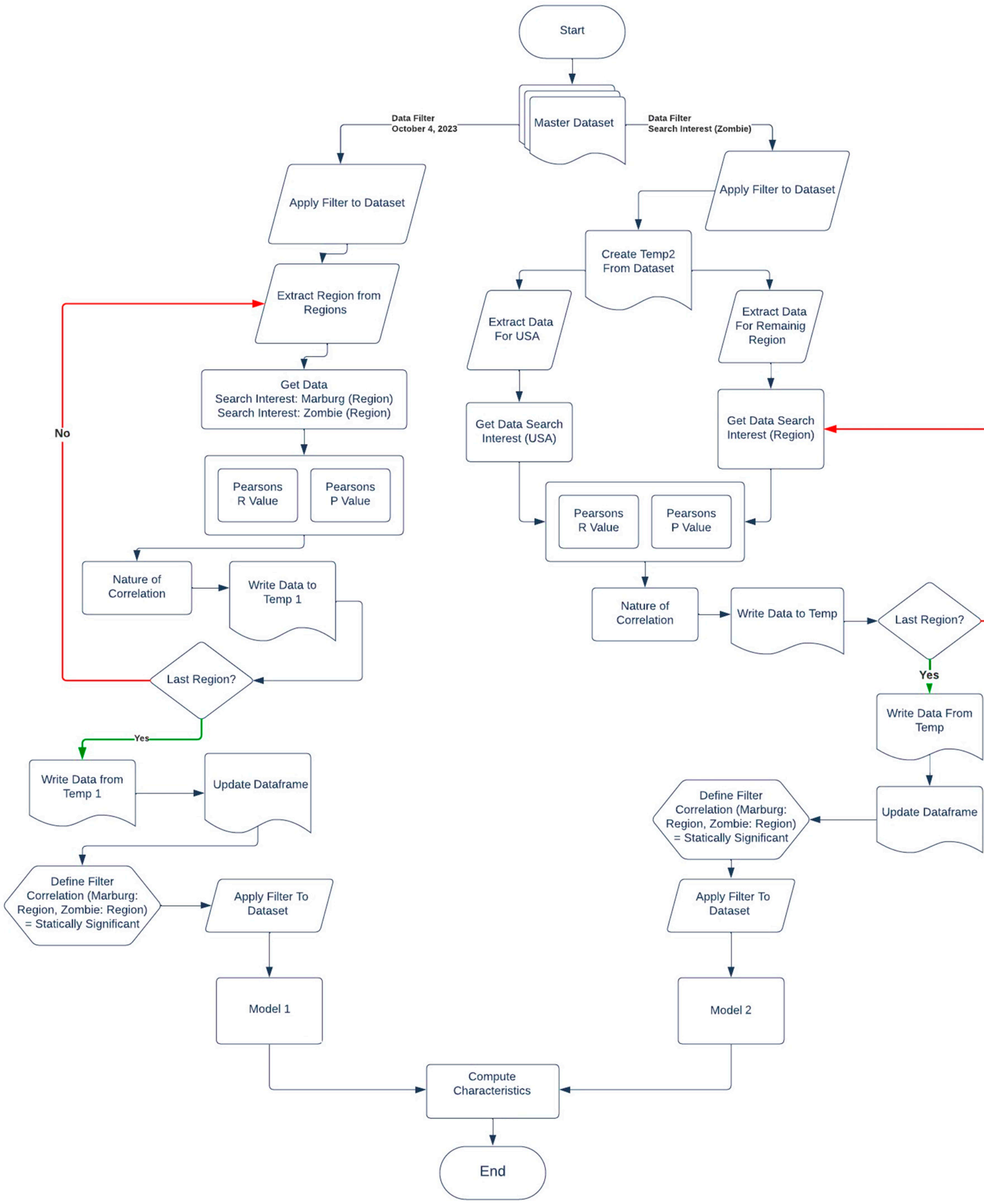

Figure 3. A flowchart that represents different forms of correlation analysis that was performed on the dataset.

4. Results and Discussion

This section presents the results and highlights the novel findings of this work. As discussed in Section 3, Algorithms 1, 2, and 3 were applied to the web behavior data related to MVD present in the dataset and the results of forecasting for each region were plotted and computed using RMSE, MSE, and MAE. As a result of the same, a graph was plotted per model per region resulting in 648 graphs (3 plots per region x 216 regions). To avoid possible redundancy, the graphs of 9 regions (selected at random) are shown in Figures 4–12, respectively.

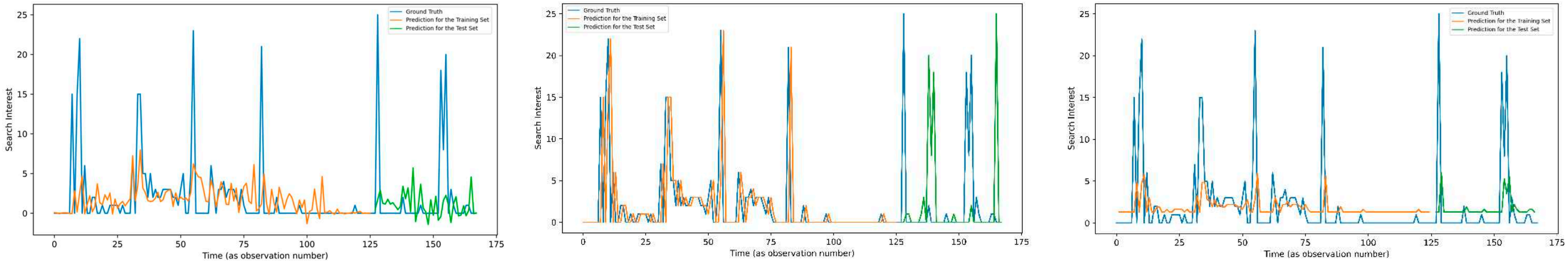

Figure 4. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Australia using Autocorrelation, ARIMA, and LSTM

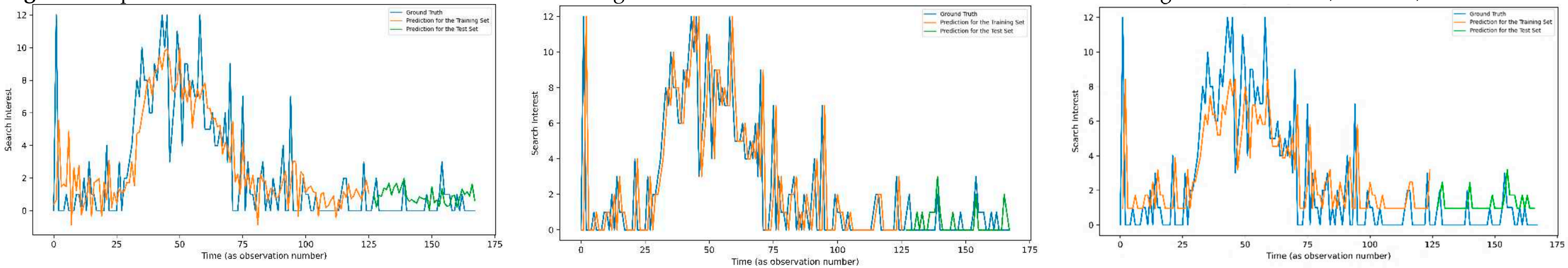

Figure 5. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Canada using Autocorrelation, ARIMA, and LSTM

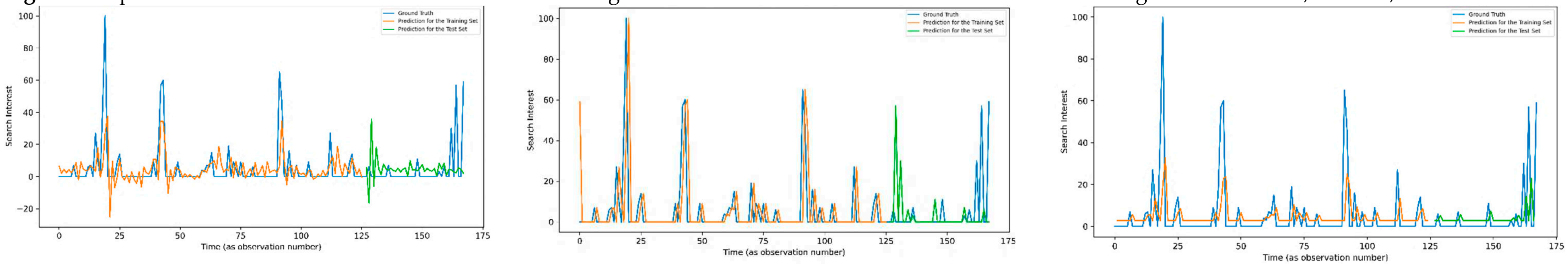

Figure 6. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Morocco using Autocorrelation, ARIMA, and LSTM

doi:10.20944/preprints202310.1998.v1

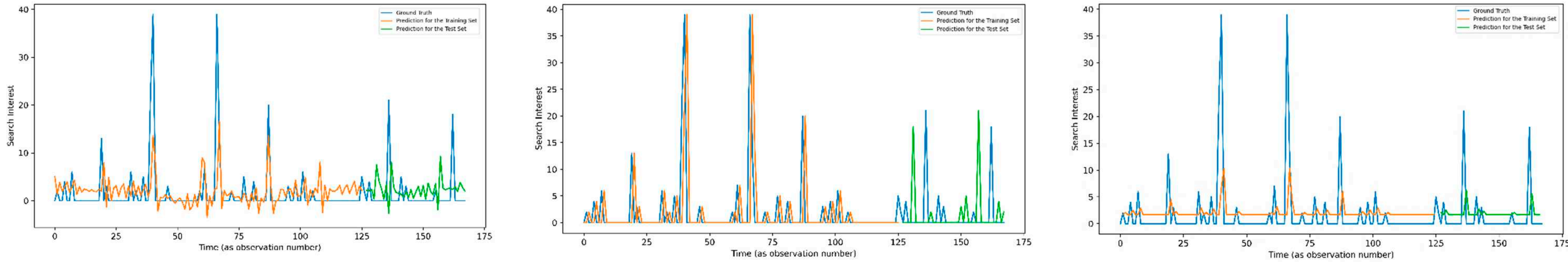

Figure 7. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Ukraine using Autocorrelation, ARIMA, and LSTM

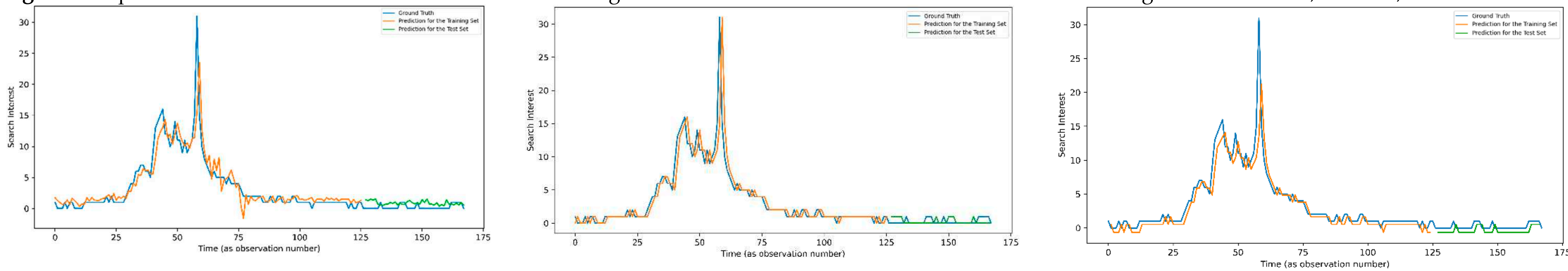

Figure 8. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in the USA using Autocorrelation, ARIMA, and LSTM

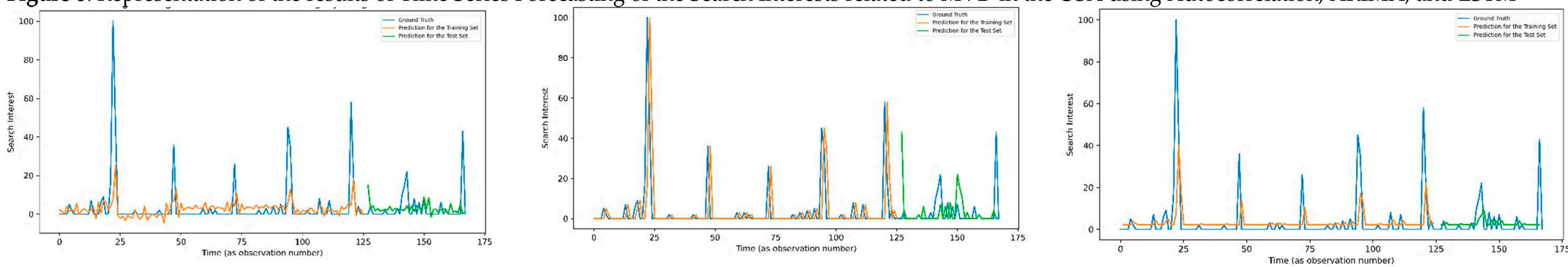

Figure 9. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Uruguay using Autocorrelation, ARIMA, and LSTM

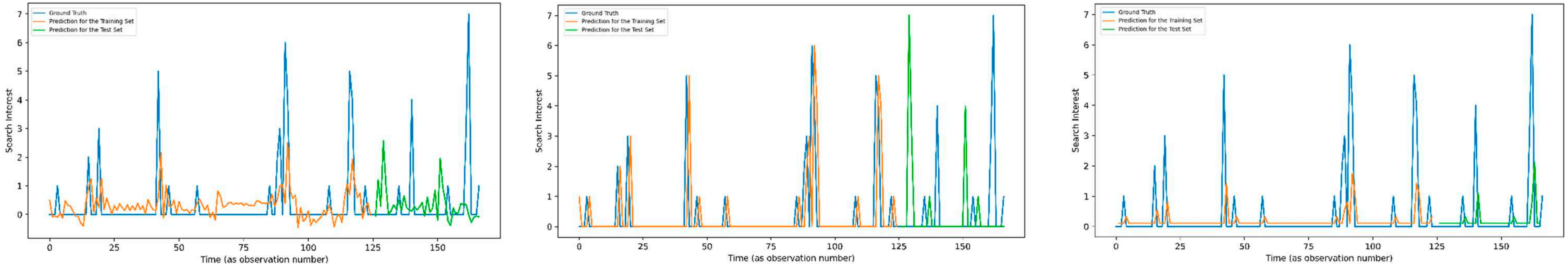

Figure 10. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Ireland using Autocorrelation, ARIMA, and LSTM

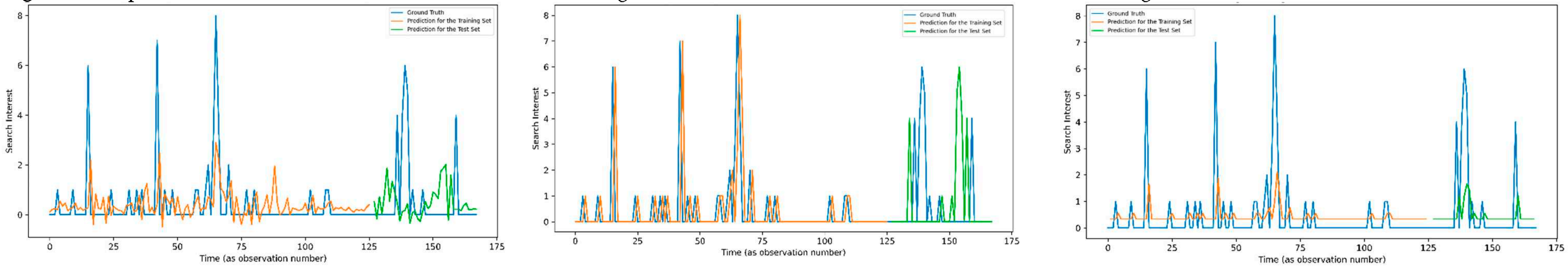

Figure 11. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in France using Autocorrelation, ARIMA, and LSTM

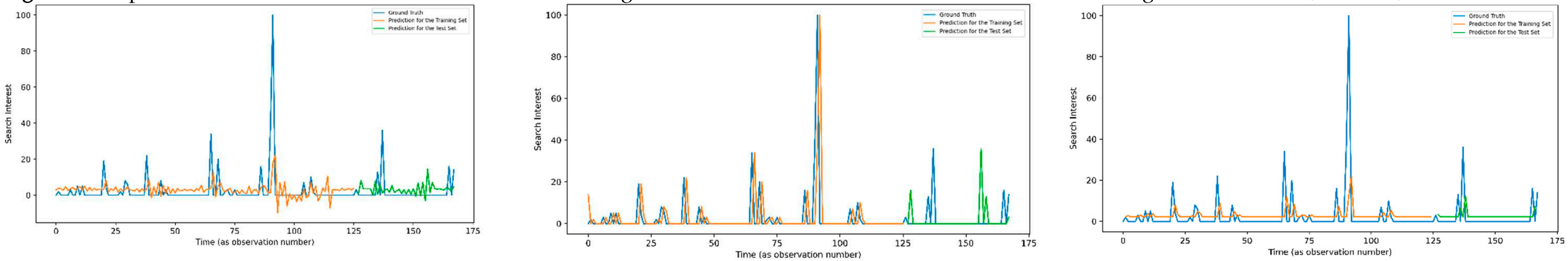

Figure 12. Representation of the results of Time Series Forecasting of the Search Interests related to MVD in Denmark using Autocorrelation, ARIMA, and LSTM

The complete results (RMSE, MSE, and MAE on Train and Test sets) of running Algorithms 1, 2, and 3 (ARIMA, Autocorrelation, and LSTM) on the data of all 216 regions are presented in Tables 2, 3, and 4, respectively.

Table 2. Results (RMSE, MSE, and MAE on Train and Test sets) of running Algorithm 1 on the master dataset.

Country Name	RMSE for ARIMA (Train Set)	MSE for ARIMA (Train Set)	MAE for ARIMA (Train Set)	RMSE for ARIMA (Test Set)	MSE for ARIMA (Test Set)	MAE for ARIMA (Test Set)
Afghanistan	0	0	0	0	0	0
Åland Islands	0	0	0	0	0	0
Albania	13.78808	190.1111	3.809524	20.00595	400.2381	6.095238
Algeria	9.59249	92.01587	3.68254	22.13272	489.8571	6.571429
American Samoa	0	0	0	0	0	0
Andorra	0	0	0	0	0	0
Angola	9.029933	81.53968	3.396825	2.488067	6.190476	0.761905
Antigua & Barbuda	16.74837	280.5079	7.253968	5.442338	29.61905	2.380952
Argentina	8.276952	68.50794	2.571429	1.091089	1.190476	0.47619
Armenia	0	0	0	0	0	0
Aruba	0	0	0	0	0	0
Australia	5.370407	28.84127	2.222222	7.309485	53.42857	2.952381
Austria	16.61277	275.9841	5.126984	5.019011	25.19048	1.809524
Azerbaijan	16.67762	278.1429	5.47619	4.396969	19.33333	2.190476
Bahamas	13.89616	193.1032	5.261905	7.857359	61.7381	3.404762
Bahrain	12.02181	144.5238	5.873016	16.74885	280.5238	8.095238
Bangladesh	7.380261	54.46825	3.801587	5.561346	30.92857	2.166667
Barbados	10.33257	106.7619	3.873016	9.209209	84.80952	3.904762
Belarus	0	0	0	0	0	0
Belgium	14.64772	214.5556	4.285714	3.070598	9.428571	0.952381
Belize	9.096485	82.74603	3.68254	6.488084	42.09524	2.904762
Benin	7.529835	56.69841	3.650794	13.73386	188.619	5.095238
Bermuda	0	0	0	0	0	0
Bhutan	12.06892	145.6587	4.833333	8.063734	65.02381	2.880952
Bolivia	11.99669	143.9206	4.047619	8.524475	72.66667	3.809524
Bosnia & Herzegovina	7.268108	52.8254	2.079365	7.057586	49.80952	2
Botswana	18.51833	342.9286	5.865079	7.851297	61.64286	3.833333
Brazil	1.339272	1.793651	0.619048	2.654735	7.047619	1.238095
British Virgin Islands	0	0	0	0	0	0
Brunei	16.08213	258.6349	5.730159	14.56512	212.1429	5.095238
Bulgaria	17.32463	300.1429	6.460317	13.12758	172.3333	5.47619
Burkina Faso	21.58924	466.0952	7.825397	6.636838	44.04762	2.904762
Burundi	9.040473	81.73016	2.984127	9.829499	96.61905	4
Cambodia	16.83628	283.4603	7.920635	15.45654	238.9048	8.809524
Cameroon	6.508846	42.36508	2.730159	24.94756	622.381	10.57143
Canada	2.875733	8.269841	1.746032	0.845154	0.714286	0.47619
Cape Verde	18.35886	337.0476	7.761905	12.40584	153.9048	6.095238
Cayman Islands	6.670237	44.49206	2.142857	5.300494	28.09524	2.380952

 doi:10.20944/preprints202310.1998.v1

Chad	8.387443	70.34921	3.047619	3.690399	13.61905	1.666667
Chile	9.139136	83.52381	1.444444	15.43651	238.2857	2.571429
China	20.72534	429.5397	9.047619	10.89779	118.7619	4.285714
Côte d'Ivoire	7.041825	49.5873	2.412698	13.30592	177.0476	5.047619
Colombia	5.540615	30.69841	1.603175	0.872872	0.761905	0.380952
Comoros	5.889188	34.68254	2.126984	6.113996	37.38095	2.714286
Congo - Brazzaville	11.52774	132.8889	3.809524	8.582929	73.66667	3.47619
Congo - Kinshasa	13.79383	190.2698	5.190476	4.918381	24.19048	2.142857
Costa Rica	11.30599	127.8254	4.619048	27.79431	772.5238	11.28571
Croatia	15.55431	241.9365	5.253968	16.54719	273.8095	5.238095
Cuba	14.12754	199.5873	5.650794	15.76615	248.5714	3.714286
Curaçao	0	0	0	0	0	0
Cyprus	14.44969	208.7937	5.142857	9.534399	90.90476	4.619048
Czechia	9.922317	98.45238	3.246032	7.453028	55.54762	3.5
Denmark	13.02013	169.5238	4.396825	9.329931	87.04762	3.571429
Djibouti	0	0	0	0	0	0
Dominica	0	0	0	0	0	0
Dominican Republic	18.38305	337.9365	6.571429	6.879922	47.33333	2.47619
Ecuador	8.286056	68.65873	2.722222	4.49603	20.21429	1.928571
Egypt	9.951868	99.03968	5.214286	7.123068	50.7381	3.404762
El Salvador	14.10449	198.9365	3.222222	2.43975	5.952381	1
Equatorial Guinea	14.94275	223.2857	5.603175	18.76547	352.1429	7.952381
Estonia	13.93238	194.1111	4.428571	22.47856	505.2857	9.333333
Eswatini	17.02706	289.9206	6.968254	21.07809	444.2857	9.333333
Ethiopia	18.62879	347.0317	7.714286	23.99603	575.8095	10.47619
Faroe Islands	0	0	0	0	0	0
Fiji	20.84523	434.5238	8.634921	13.99149	195.7619	6.428571
Finland	7.618899	58.04762	2.412698	3.450328	11.90476	1.52381
France	1.480026	2.190476	0.603175	1.647509	2.714286	0.761905
French Guiana	0	0	0	0	0	0
French Polynesia	0	0	0	0	0	0
Gabon	8.54679	73.04762	3.142857	14.2361	202.6667	6.095238
Gambia	14.50999	210.5397	5.968254	11.53256	133	3.952381
Georgia	15.58082	242.7619	5.587302	5.550633	30.80952	2.190476
Germany	2.173067	4.722222	1.18254	2.198484	4.833333	1.214286
Ghana	13.6376	185.9841	7.095238	25.91837	671.7619	11.66667
Gibraltar	0	0	0	0	0	0
Greece	7.662525	58.71429	2.857143	19.79177	391.7143	7.238095
Greenland	0	0	0	0	0	0
Grenada	14.38363	206.8889	4.47619	12.02775	144.6667	4.619048
Guadeloupe	5.747325	33.03175	2.126984	2.115701	4.47619	0.666667
Guam	0	0	0	0	0	0
Guatemala	14.58799	212.8095	5.365079	5.89996	34.80952	2.380952
Guernsey	0	0	0	0	0	0
Guinea	12.59567	158.6508	5.285714	11.49534	132.1429	4.952381
Guinea-Bissau	17.11956	293.0794	4.952381	12.12828	147.0952	4.333333
Guyana	9.763066	95.31746	1.857143	14.83561	220.0952	2.619048

Haiti	10.07433	101.4921	3.650794	1.690309	2.857143	0.761905
Honduras	11.29827	127.6508	4.31746	9.892277	97.85714	3.952381
Hong Kong	10.86497	118.0476	4.460317	9.170346	84.09524	3.52381
Hungary	7.077799	50.09524	2.936508	15.23155	232	6.571429
Iceland	8.991177	80.84127	3.619048	28.24721	797.9048	9.142857
India	1.939563	3.761905	0.888889	0.9759	0.952381	0.380952
Indonesia	1.425393	2.031746	0.809524	1.195229	1.428571	0.714286
Iran	8.369446	70.04762	3.31746	6.33208	40.09524	3.238095
Iraq	17.57027	308.7143	8.126984	12.94126	167.4762	6.380952
Ireland	1.268069	1.608	0.488	1.625687	2.642857	0.642857
Isle of Man	0	0	0	0	0	0
Israel	11.54494	133.2857	5.031746	19.18705	368.1429	10.2381
Italy	4.059087	16.47619	1.888889	2.77746	7.714286	1.142857
Jamaica	6.163126	37.98413	2.873016	10.28175	105.7143	3.857143
Japan	11.6585	135.9206	4.492063	13.88216	192.7143	5.095238
Jersey	0	0	0	0	0	0
Jordan	5.61602	31.53968	2.206349	9.337584	87.19048	3.571429
Kazakhstan	0	0	0	0	0	0
Kenya	9.204899	84.73016	3.968254	16.88617	285.1429	8
Kosovo	8.073079	65.1746	2.15873	9.623879	92.61905	3.52381
Kuwait	15.4509	238.7302	7	24.9819	624.0952	10.85714
Kyrgyzstan	0	0	0	0	0	0
Laos	0	0	0	0	0	0
Latvia	12.78454	163.4444	4.492063	21.67839	469.9524	6.619048
Lebanon	16.85701	284.1587	6.285714	7.412987	54.95238	2.380952
Lesotho	11.6986	136.8571	5.365079	26.57245	706.0952	12.90476
Liberia	11.81303	139.5476	5.039683	16.28248	265.119	7.833333
Libya	10.5492	111.2857	5.190476	11.81605	139.619	4.809524
Liechtenstein	0	0	0	0	0	0
Lithuania	11.90038	141.619	3.809524	6.45866	41.71429	2.380952
Luxembourg	6.737717	45.39683	2	24.15919	583.6667	10.2381
Macao	14.08985	198.5238	4.285714	6.561068	43.04762	2.190476
Madagascar	11.76894	138.5079	3.52381	25.11213	630.619	9.190476
Malawi	13.69973	187.6825	4.603175	17.36718	301.619	6.095238
Malaysia	4.101877	16.8254	2.222222	4.649629	21.61905	2
Maldives	12.7895	163.5714	4.301587	21.52629	463.381	9.333333
Mali	10.19103	103.8571	3.873016	19.22548	369.619	10.90476
Malta	13.12093	172.1587	4.857143	5.191568	26.95238	2.285714
Martinique	12.62336	159.3492	4.285714	29.56188	873.9048	13.38095
Mauritania	20.30404	412.254	8.761905	12.12043	146.9048	4.857143
Mauritius	12.63593	159.6667	4.777778	24.51336	600.9048	11.04762
Mexico	4.037522	16.30159	1.380952	1.759329	3.095238	1
Moldova	0	0	0	0	0	0
Mongolia	8.125504	66.02381	2.626984	4.753445	22.59524	2.214286
Montenegro	13.7708	189.6349	3.444444	8.799351	77.42857	3.142857
Morocco	17.04033	290.373	7.309524	17.09985	292.4048	7.119048
Mozambique	11.9227	142.1508	3.007937	8.617535	74.2619	3.595238

Myanmar (Burma)	9.760627	95.26984	2.349206	15.51497	240.7143	3.047619
Namibia	12.94524	167.5794	4.944444	22.81969	520.7381	7.166667
Nepal	16.66381	277.6825	6.52381	4.353433	18.95238	1.428571
Netherlands	15.66363	245.3492	4.52381	10.36937	107.5238	4.333333
New Caledonia	0	0	0	0	0	0
New Zealand	6.948792	48.28571	3.047619	10.13246	102.6667	3.904762
Nicaragua	5.087333	25.88095	1.515873	1.870829	3.5	0.880952
Niger	4.739232	22.46032	1.809524	22.90872	524.8095	7.52381
Nigeria	9.814955	96.33333	3.888889	9.763879	95.33333	3.52381
North Macedonia	14.08928	198.5079	4.063492	4.203173	17.66667	1.857143
Northern Mariana Islands	0	0	0	0	0	0
Norway	8.161563	66.61111	3.02381	4.896549	23.97619	2.309524
Oman	12.69921	161.2698	5.666667	21.22218	450.381	8.52381
Pakistan	9.568467	91.55556	3.349206	6.06316	36.7619	2.190476
Palestine	0	0	0	0	0	0
Panama	14.65097	214.6508	5.444444	18	324	5.571429
Papua New Guinea	0	0	0	0	0	0
Paraguay	15.67882	245.8254	4.984127	18.52926	343.3333	7.190476
Peru	10.9982	120.9603	3.738095	1.779513	3.166667	0.833333
Philippines	1.43095	2.047619	0.714286	2.035401	4.142857	0.809524
Poland	4.712361	22.20635	1.920635	6.611678	43.71429	2.952381
Portugal	15.74348	247.8571	5.730159	13.20714	174.4286	4.428571
Puerto Rico	15.98064	255.381	5.809524	2.21467	4.904762	0.904762
Qatar	15.13694	229.127	6.047619	30.71451	943.381	12.71429
Réunion	13.52159	182.8333	4.277778	12.2756	150.6905	5.880952
Romania	5.274978	27.8254	2.412698	9.162553	83.95238	3.190476
Russia	3.825561	14.63492	1.333333	1.889822	3.571429	0.904762
Rwanda	19.74721	389.9524	6.555556	19.97141	398.8571	9.571429
Samoa	0	0	0	0	0	0
San Marino	0	0	0	0	0	0
Saudi Arabia	13.8587	192.0635	6.666667	11.56966	133.8571	5.952381
Senegal	17.12605	293.3016	6.507937	5.928141	35.14286	2.809524
Serbia	10.56123	111.5397	3.47619	23.95929	574.0476	8.666667
Seychelles	13.68118	187.1746	5.936508	16.06831	258.1905	7.047619
Sierra Leone	16.17881	261.754	4.97619	17.98611	323.5	8.02381
Singapore	4.708149	22.16667	1.642857	6.559254	43.02381	2.738095
Sint Maarten	0	0	0	0	0	0
Slovakia	18.30973	335.246	7.357143	12.3645	152.881	4.738095
Slovenia	16.02379	256.7619	5.571429	16.71754	279.4762	6.285714
Solomon Islands	0	0	0	0	0	0
Somalia	7.06433	49.90476	3.285714	21.97726	483	9.571429
South Africa	4.974538	24.74603	2.761905	8.745067	76.47619	3.809524
South Korea	10.1848	103.7302	4.698413	8.807464	77.57143	4.952381
South Sudan	15.41799	237.7143	5.079365	14.0153	196.4286	7.095238
Spain	2.817181	7.936508	1.15873	1.812654	3.285714	0.809524
Sri Lanka	19.99127	399.6508	7.888889	12.70171	161.3333	4.952381
St. Barthe_lemy	0	0	0	0	0	0

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St. Helena	20.96747	439.6349	11.09524	20.79034	432.2381	9.857143
St. Kitts & Nevis	0	0	0	0	0	0
St. Lucia	6.988653	48.84127	2.619048	22.619	511.619	6.952381
St. Martin	0	0	0	0	0	0
St. Pierre & Miquelon	0	0	0	0	0	0
St. Vincent & Grenadines	11.6046	134.6667	2.84127	15.86551	251.7143	4.190476
Sudan	20.89182	436.4683	9.452381	14.86046	220.8333	8.261905
Suriname	0	0	0	0	0	0
Sweden	13.94661	194.5079	4.650794	9.795529	95.95238	2.761905
Switzerland	14.39246	207.1429	4.111111	14.48973	209.9524	3.857143
Syria	0	0	0	0	0	0
Taiwan	12.05543	145.3333	5.31746	2.581989	6.666667	1.238095
Tajikistan	0	0	0	0	0	0
Tanzania	20.46949	419	6.968254	26.45301	699.7619	13.19048
Thailand	2.603417	6.777778	1.015873	2.78602	7.761905	1.190476
Timor-Leste	0	0	0	0	0	0
Togo	15.50627	240.4444	5.714286	26.70741	713.2857	11.7619
Trinidad & Tobago	11.38294	129.5714	4.428571	33.98669	1155.095	16.71429
Türkiye	2.134375	4.555556	0.968254	2.845213	8.095238	1.190476
Tunisia	17.81341	317.3175	6.47619	22.72192	516.2857	7.333333
Turkmenistan	0	0	0	0	0	0
Turks & Caicos Islands	0	0	0	0	0	0
U.S. Virgin Islands	0	0	0	0	0	0
Uganda	16.43216	270.0159	6.920635	29.3428	861	12.52381
Ukraine	7.148648	51.10317	2.849206	6.269731	39.30952	2.642857
United Arab Emirates	13.60964	185.2222	6.984127	10.91962	119.2381	4.380952
United Kingdom	0.629941	0.396825	0.285714	0.899735	0.809524	0.238095
United States	2.33843	5.468254	0.928571	0.46291	0.214286	0.214286
Uruguay	14.211	201.9524	5.285714	10.68154	114.0952	4.904762
Uzbekistan	14.3737	206.6032	3.873016	8.41201	70.7619	3.47619
Vanuatu	0	0	0	0	0	0
Venezuela	9.136531	83.47619	2.301587	5.830952	34	1.809524
Vietnam	2.081666	4.333333	0.857143	2.171241	4.714286	1
Western Sahara	0	0	0	0	0	0
Yemen	0	0	0	0	0	0
Zambia	13.4772	181.6349	5.698413	14.46342	209.1905	6.285714
Zimbabwe	12.54832	157.4603	5.190476	14.32613	205.2381	6.380952

Table 3. Results (RMSE, MSE, and MAE on Train and Test sets) of running Algorithm 2 on the master dataset.

Country Name	RMSE of Autocorrelation (Train Set)	MSE of Autocorrelation (Train Set)	MAE of Autocorrelation (Train Set)	RMSE of Autocorrelation (Test Set)	MSE of Autocorrelation (Test Set)	MAE of Autocorrelation (Test Set)
Afghanistan	0	0	0	0	0	0
Aland Islands	0	0	0	0	0	0
Albania	9.547236	266.6762	3.449842	16.33022	266.6762	6.070559
Algeria	5.983334	309.8742	3.026799	17.60324	309.8742	8.755387

 doi:10.20944/preprints202310.1998.v1

American Samoa	0	0	0	0	0	0
Andorra	0	0	0	0	0	0
Angola	6.06661	31.05337	3.182088	5.572555	31.05337	3.188894
Antigua & Barbuda	10.53139	29.9032	5.786529	5.468382	29.9032	4.685652
Argentina	5.160407	3.124834	1.915264	1.76772	3.124834	0.977066
Armenia	0	0	0	0	0	0
Aruba	0	0	0	0	0	0
Australia	4.096864	33.99733	2.078919	5.830723	33.99733	2.770755
Austria	10.83433	22.50378	4.518217	4.743815	22.50378	3.749277
Azerbaijan	11.01557	13.87758	3.86089	3.725262	13.87758	3.252013
Bahamas	9.789052	48.23301	5.390787	6.944999	48.23301	4.775422
Bahrain	8.451745	203.8561	6.220559	14.27782	203.8561	9.989248
Bangladesh	4.524827	24.08574	2.864864	4.907722	24.08574	3.710554
Barbados	8.051779	44.85521	2.938033	6.697403	44.85521	2.92712
Belarus	0	0	0	0	0	0
Belgium	8.85279	8.422725	2.9068	2.902193	8.422725	2.344049
Belize	6.027706	22.24202	3.190105	4.716145	22.24202	2.821407
Benin	4.729482	112.321	2.869876	10.59816	112.321	4.86543
Bermuda	0	0	0	0	0	0
Bhutan	7.641408	61.58425	4.080188	7.847563	61.58425	4.348069
Bolivia	8.978993	41.01737	4.208674	6.404481	41.01737	3.756414
Bosnia & Herzegovina	4.779151	28.62655	1.992647	5.350379	28.62655	2.262842
Botswana	12.67149	78.44828	6.246121	8.857103	78.44828	6.110068
Brazil	0.882356	3.935664	0.516444	1.983851	3.935664	0.931681
British Virgin Islands	0	0	0	0	0	0
Brunei	9.480926	308.6751	4.700313	17.56915	308.6751	8.426272
Bulgaria	11.95635	83.69336	6.315804	9.148408	83.69336	6.237365
Burkina Faso	14.31467	41.75848	7.148378	6.46208	41.75848	5.400082
Burundi	7.373451	65.44432	3.422807	8.089767	65.44432	5.022543
Cambodia	11.88999	345.2464	8.282581	18.58081	345.2464	12.45667
Cameroon	4.86618	348.1162	2.915288	18.65787	348.1162	9.084295
Canada	2.264004	0.868871	1.600211	0.932133	0.868871	0.783274
Cape Verde	11.46525	110.7488	5.873995	10.52372	110.7488	6.187318
Cayman Islands	5.534619	22.40385	2.6401	4.73327	22.40385	3.189553
Chad	5.274818	10.57232	2.418889	3.25151	10.57232	1.981079
Chile	1.705141	237.0363	0.797758	15.39598	237.0363	3.170539
China	14.75331	128.8751	8.077444	11.35232	128.8751	7.216554
Côte d’Ivoire	9.282463	432.434	3.350107	20.79505	432.434	11.19471
Colombia	3.824796	1.991984	1.483824	1.411377	1.991984	1.206169
Comoros	4.57128	52.32465	2.782305	7.233578	52.32465	4.655305
Congo - Brazzaville	7.258426	54.2349	3.104642	7.364435	54.2349	3.767057
Congo - Kinshasa	9.466793	17.27012	4.488946	4.155734	17.27012	3.452318

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Costa Rica	6.153947	677.8751	3.521392	26.03604	677.8751	14.58405
Croatia	9.937297	322.4361	4.849895	17.95651	322.4361	8.571793
Cuba	9.673677	115.8269	4.788526	10.76229	115.8269	3.96974
Curaçao	0	0	0	0	0	0
Cyprus	10.9392	105.7162	5.734284	10.28184	105.7162	7.269532
Czechia	6.525328	38.41361	2.827252	6.197872	38.41361	3.605674
Denmark	9.850139	56.46845	4.841825	7.514549	56.46845	4.829783
Djibouti	0	0	0	0	0	0
Dominica	0	0	0	0	0	0
Dominican Republic	12.21003	51.48443	5.875481	7.175265	51.48443	5.859984
Ecuador	5.591392	15.12805	2.355274	3.889479	15.12805	2.040708
Egypt	6.149146	45.76967	4.304301	6.765329	45.76967	4.941281
El Salvador	47.795	4031.202	17.61659	63.49175	4031.202	28.50461
Equatorial Guinea	10.05492	185.1663	4.273236	13.60758	185.1663	6.827011
Estonia	9.493435	320.6342	4.461361	17.90626	320.6342	10.35126
Eswatini	10.11582	292.2951	5.50259	17.09664	292.2951	8.906344
Ethiopia	11.90093	255.0395	7.506921	15.96996	255.0395	8.341224
Faroe Islands	0	0	0	0	0	0
Fiji	14.37325	132.6001	7.861227	11.51521	132.6001	7.789546
Finland	5.233477	6.194874	2.325577	2.488951	6.194874	1.932455
France	1.120485	2.003828	0.607629	1.415566	2.003828	0.863699
French Guiana	0	0	0	0	0	0
French Polynesia	0	0	0	0	0	0
Gabon	6.045124	165.8478	3.727497	12.87819	165.8478	7.123294
Gambia	9.52169	71.51402	5.396629	8.456596	71.51402	5.872677
Georgia	12.25343	100.2455	7.121271	10.01227	100.2455	7.364313
Germany	1.575677	2.520911	1.036421	1.587738	2.520911	1.119649
Ghana	8.127446	471.2825	5.614317	21.70904	471.2825	13.16765
Gibraltar	0	0	0	0	0	0
Greece	5.555145	244.8915	2.747845	15.64901	244.8915	7.481647
Greenland	0	0	0	0	0	0
Grenada	12.86441	151.6387	6.159252	12.31417	151.6387	8.262845
Guadeloupe	4.134032	3.222124	1.949929	1.795028	3.222124	1.376126
Guam	0	0	0	0	0	0
Guatemala	9.344646	29.69501	5.26385	5.449313	29.69501	4.369718
Guernsey	0	0	0	0	0	0
Guinea	8.020519	95.65707	4.661525	9.780443	95.65707	5.539834
Guinea-Bissau	11.16234	85.9241	4.971446	9.269526	85.9241	4.876213
Guyana	2.517421	235.7208	0.902204	15.3532	235.7208	3.061355
Haiti	6.585808	6.792683	3.144837	2.606278	6.792683	2.40467
Honduras	9.296952	57.77398	4.400755	7.60092	57.77398	4.649517
Hong Kong	7.353977	41.40477	3.82363	6.434654	41.40477	3.466788
Hungary	5.225407	122.7043	3.140391	11.0772	122.7043	5.309302
Iceland	5.922715	419.9142	3.113922	20.49181	419.9142	8.49435

India	1.289805	0.900497	0.749746	0.948945	0.900497	0.731705
Indonesia	1.103112	0.782783	0.686736	0.88475	0.782783	0.668795
Iran	5.515225	31.68146	2.994191	5.628629	31.68146	3.877756
Iraq	12.55775	87.60657	7.057821	9.359838	87.60657	6.396014
Ireland	0.974491	1.729115	0.547556	1.314958	1.729115	0.70643
Isle of Man	0	0	0	0	0	0
Israel	7.903272	196.6148	4.960509	14.02194	196.6148	8.713525
Italy	3.133917	4.316491	1.612017	2.077617	4.316491	1.404546
Jamaica	4.290459	71.54644	2.75134	8.458513	71.54644	5.632011
Japan	7.735241	106.0027	4.238804	10.29576	106.0027	4.884764
Jersey	0	0	0	0	0	0
Jordan	3.708129	86.17836	1.7919	9.28323	86.17836	4.655009
Kazakhstan	0	0	0	0	0	0
Kenya	5.960261	137.8703	3.875778	11.74182	137.8703	7.767086
Kosovo	6.359459	49.82043	1.686356	7.058359	49.82043	3.073302
Kuwait	10.19731	714.7134	6.009618	26.73413	714.7134	15.32199
Kyrgyzstan	0	0	0	0	0	0
Laos	0	0	0	0	0	0
Latvia	8.898493	233.3365	4.326054	15.27536	233.3365	6.396053
Lebanon	11.15287	53.26224	5.987507	7.298098	53.26224	5.779635
Lesotho	7.575091	401.5749	4.781264	20.03934	401.5749	10.72093
Liberia	7.775482	175.9486	4.44222	13.26456	175.9486	8.237929
Libya	7.048344	111.3744	4.542626	10.55341	111.3744	5.525318
Liechtenstein	0	0	0	0	0	0
Lithuania	9.031481	24.0281	3.696522	4.901846	24.0281	2.652109
Luxembourg	5.203751	584.4337	2.55309	24.17506	584.4337	11.75841
Macao	16.37218	626.3795	7.214573	25.02758	626.3795	12.00941
Madagascar	8.056012	373.3813	3.166608	19.32308	373.3813	9.879311
Malawi	9.456212	214.1751	4.590584	14.63472	214.1751	6.548388
Malaysia	3.027362	14.55967	1.985457	3.815713	14.55967	2.213564
Maldives	11.05308	538.4476	5.323819	23.20447	538.4476	13.88415
Mali	7.121835	306.3747	4.064986	17.50356	306.3747	11.27971
Malta	9.056621	31.83283	4.657467	5.642059	31.83283	4.712883
Martinique	9.748098	689.4085	5.245546	26.25659	689.4085	15.4876
Mauritania	13.13171	88.15271	7.200627	9.388968	88.15271	7.662908
Mauritius	8.761748	453.3572	3.836104	21.29219	453.3572	11.63681
Mexico	2.612147	2.922535	1.126163	1.709542	2.922535	1.043981
Moldova	0	0	0	0	0	0
Mongolia	5.169104	11.07499	2.21608	3.32791	11.07499	2.116271
Montenegro	10.46805	102.2567	4.440561	10.11221	102.2567	6.26818
Morocco	12.27848	241.1229	6.936316	15.52813	241.1229	8.58022
Mozambique	8.961407	35.63636	2.413428	5.969619	35.63636	2.639244
Myanmar (Burma)	2.407638	235.912	1.352414	15.35943	235.912	3.643141
Namibia	7.874785	239.0842	4.49069	15.46235	239.0842	6.310737
Nepal	12.96567	29.01789	5.968387	5.386826	29.01789	3.733779

Netherlands	10.6473	61.49948	4.320568	7.842161	61.49948	4.930311
New Caledonia	0	0	0	0	0	0
New Zealand	5.092617	77.35123	2.885639	8.794955	77.35123	5.253943
Nicaragua	3.552405	1.662006	1.395157	1.289188	1.662006	0.812994
Niger	3.915178	266.4439	1.529212	16.32311	266.4439	4.886317
Nigeria	6.694565	52.00449	4.023198	7.211414	52.00449	4.40873
North Macedonia	10.75917	13.58104	3.545521	3.685246	13.58104	2.548404
Northern Mariana Islands	0	0	0	0	0	0
Norway	5.832329	14.17639	2.866471	3.765155	14.17639	2.452245
Oman	7.612618	479.1339	4.955876	21.88913	479.1339	10.12697
Pakistan	6.305306	46.19294	3.045765	6.796539	46.19294	4.200318
Palestine	0	0	0	0	0	0
Panama	7.976283	265.3628	5.033874	16.28996	265.3628	8.038425
Papua New Guinea	0	0	0	0	0	0
Paraguay	9.36601	264.2494	4.172757	16.25575	264.2494	6.955869
Peru	7.624232	5.534475	3.702979	2.352547	5.534475	2.082666
Philippines	0.885505	3.714283	0.54972	1.927247	3.714283	1.078276
Poland	3.660544	29.904	2.081432	5.468454	29.904	2.813396
Portugal	10.46164	101.0983	5.017028	10.05477	101.0983	5.165927
Puerto Rico	10.56894	16.33975	4.928882	4.042246	16.33975	3.629358
Qatar	11.173	452.4833	6.37943	21.27166	452.4833	10.9481
Réunion	8.809801	73.17947	3.499218	8.554501	73.17947	4.389758
Romania	3.335597	44.26107	2.133118	6.652899	44.26107	3.023861
Russia	2.254237	3.029526	1.0317	1.740553	3.029526	1.230431
Rwanda	11.03336	237.3087	4.619325	15.40483	237.3087	7.975922
Samoa	0	0	0	0	0	0
San Marino	0	0	0	0	0	0
Saudi Arabia	9.002735	77.40342	5.940556	8.797921	77.40342	6.727711
Senegal	11.0033	35.37583	5.909475	5.947758	35.37583	4.661211
Serbia	7.371186	269.5461	3.115696	16.41786	269.5461	6.858306
Seychelles	8.71973	166.6366	5.428664	12.90878	166.6366	8.045354
Sierra Leone	10.5304	186.5661	4.744025	13.65892	186.5661	7.072295
Singapore	3.037643	21.66193	1.64868	4.654238	21.66193	2.354216
Sint Maarten	0	0	0	0	0	0
Slovakia	13.65778	174.2823	7.24118	13.2016	174.2823	6.851287
Slovenia	10.04812	190.0684	4.762657	13.78653	190.0684	7.438249
Solomon Islands	0	0	0	0	0	0
Somalia	5.218272	314.7882	3.14686	17.74227	314.7882	8.515299
South Africa	3.03295	81.68939	2.224909	9.038219	81.68939	5.821945
South Korea	6.544425	42.94735	4.220322	6.553423	42.94735	4.802469
South Sudan	10.60482	110.5208	5.30904	10.51289	110.5208	6.626357

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Spain	1.771953	3.135097	0.968608	1.770621	3.135097	1.226833
Sri Lanka	13.79162	122.2438	8.492347	11.05639	122.2438	9.245106
St. Barthélemy	0	0	0	0	0	0
St. Helena	15.04679	340.1374	11.16958	18.44281	340.1374	13.80565
St. Kitts & Nevis	0	0	0	0	0	0
St. Lucia	4.452625	297.2686	2.350638	17.24148	297.2686	7.538465
St. Martin	0	0	0	0	0	0
St. Pierre & Miquelon	0	0	0	0	0	0
St. Vincent & Grenadines	6.327033	278.5168	2.980384	16.68882	278.5168	6.829061
Sudan	13.20677	120.0613	7.874987	10.95725	120.0613	7.766244
Suriname	0	0	0	0	0	0
Sweden	11.12028	58.18556	5.451402	7.627945	58.18556	4.439981
Switzerland	9.620514	106.2319	4.179798	10.30689	106.2319	4.711903
Syria	0	0	0	0	0	0
Taiwan	8.542505	15.32091	4.834299	3.914193	15.32091	3.708639
Tajikistan	0	0	0	0	0	0
Tanzania	13.1928	315.0844	5.843148	17.75062	315.0844	8.659294
Thailand	1.851518	4.061004	0.964724	2.015193	4.061004	1.023623
Timor-Leste	0	0	0	0	0	0
Togo	12.46273	797.6442	6.573539	28.2426	797.6442	16.86038
Trinidad & Tobago	7.231444	603.9144	3.430544	24.57467	603.9144	10.77016
Türkiye	1.404136	3.480567	0.863614	1.865628	3.480567	0.956541
Tunisia	12.71008	298.4444	7.344201	17.27554	298.4444	11.5082
Turkmenistan	0	0	0	0	0	0
Turks & Caicos Islands	0	0	0	0	0	0
U.S. Virgin Islands	0	0	0	0	0	0
Uganda	11.36024	450.5361	6.53962	21.22584	450.5361	8.999745
Ukraine	5.236922	22.31077	2.880307	4.723428	22.31077	3.211289
United Arab Emirates	9.81296	83.8914	6.364535	9.159225	83.8914	6.592083
United Kingdom	0.502379	0.518618	0.357571	0.720152	0.518618	0.395022
United States	2.039879	0.648399	1.119234	0.805232	0.648399	0.716547
Uruguay	11.51783	67.03862	4.861215	8.187712	67.03862	4.772031
Uzbekistan	11.15424	32.51257	3.755985	5.70198	32.51257	3.538633
Vanuatu	0	0	0	0	0	0
Venezuela	6.573665	18.05486	2.575041	4.249101	18.05486	2.422974
Vietnam	1.382188	3.861088	0.888741	1.964965	3.861088	1.055109
Western Sahara	0	0	0	0	0	0
Yemen	0	0	0	0	0	0
Zambia	9.028182	153.7403	5.60782	12.3992	153.7403	7.333309

 doi:10.20944/preprints202310.1998.v1

Zimbabwe	7.700711	137.9502	4.806979	11.74522	137.9502	7.465501

Table 4. Results (RMSE, MSE, and MAE on Train and Test sets) of running Algorithm 3 on the master dataset.

Country Name	RSME for LSTM (Train Set)	MSE for LSTM (Train Set)	MAE for LSTM (Train Set)	RSME for LSTM (Test Set)	MSE for LSTM (Test Set)	MAE for LSTM (Test Set)
Afghanistan	0	0	0	0	0	0
Åland Islands	0	0	0	0	0	0
Albania	9.7336	94.7436	3.5539	16.6119	275.9568	5.6548
Algeria	6.6306	43.9647	3.5466	15.7074	246.7213	5.0684
American Samoa	0	0	0	0	0	0
Andorra	0	0	0	0	0	0
Angola	6.4459	41.5499	3.3475	2.4405	5.956	2.2836
Antigua & Barbuda	11.0468	122.031	6.0127	4.8425	23.4496	4.6417
Argentina	5.7685	33.2755	2.3629	1.5811	2.4999	1.5477
Armenia	0	0	0	0	0	0
Aruba	0	0	0	0	0	0
Australia	4.1825	17.493	2.2748	5.5779	31.113	2.8582
Austria	11.5956	134.458	4.6221	4.0483	16.3884	3.0249
Azerbaijan	11.5166	132.6323	4.5556	3.4383	11.8218	2.9832
Bahamas	9.9308	98.6212	5.095	6.1092	37.3224	4.3574
Bahrain	8.9706	80.4724	6.1036	11.9741	143.38	7.3561
Bangladesh	4.8026	23.0654	2.796	3.8962	15.1806	2.4461
Barbados	7.2388	52.4007	2.9072	6.7102	45.0273	3.4134
Belarus	0	0	0	0	0	0
Belgium	10.2021	104.0831	3.7289	3.159	9.9791	2.926
Belize	5.5824	31.1636	2.9676	4.4613	19.9031	2.6012
Benin	5.1852	26.8863	3.2811	9.9706	99.4121	4.3851
Bermuda	0	0	0	0	0	0
Bhutan	7.9446	63.1166	4.1197	2.9389	8.6371	2.5615
Bolivia	9.2951	86.3995	4.4767	6.4988	42.2346	4.119
Bosnia & Herzegovina	5.0982	25.9919	1.9803	5.0099	25.0987	1.9786
Botswana	13.3231	177.504	5.5976	5.7334	32.8716	4.4417
Brazil	0.9128	0.8331	0.527	1.8464	3.4091	0.7874
British Virgin Islands	0	0	0	0	0	0
Brunei	9.7336	94.7437	4.1091	7.5546	57.0713	3.8908
Bulgaria	12.4939	156.0973	6.1303	9.1211	83.1944	5.3772
Burkina Faso	15.8841	252.3046	7.2073	5.3209	28.3122	4.2953
Burundi	6.3309	40.08	2.5513	6.8236	46.5612	3.018
Cambodia	11.8045	139.3459	6.8832	9.143	83.6081	7.0224
Cameroon	5.1216	26.2312	2.9666	18.5825	345.3106	7.9996
Canada	2.6211	6.87	1.8806	1.1596	1.3447	1.0067
Cape Verde	12.4699	155.4981	6.69	10.1468	102.9573	6.2734

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Cayman Islands	4.6226	21.3684	1.9359	3.6719	13.4827	1.9941
Chad	5.8912	34.7066	2.7076	3.1258	9.7707	2.112
Chile	1.7669	3.122	0.5652	0.3484	0.1214	0.2118
China	15.108	228.2521	8.4072	8.1723	66.7864	6.0264
Colombia	3.9174	15.3456	1.5493	0.9076	0.8236	0.8517
Comoros	4.5292	20.5136	2.1552	4.7915	22.9588	2.7124
Congo - Brazzaville	7.8349	61.3854	3.3439	4.1571	17.2815	2.6733
Congo - Kinshasa	9.666	93.4313	5.0803	4.2111	17.7335	3.7272
Costa Rica	6.258	39.1631	3.4591	18.6752	348.7649	6.6876
Côte d'Ivoire	4.8461	23.4845	1.9603	9.3519	87.4575	3.6104
Croatia	11.0201	121.4419	4.758	16.1631	261.2445	6.0549
Cuba	8.7039	75.7581	4.2015	11.2715	127.0462	4.359
Curaçao	0	0	0	0	0	0
Cyrpus	10.738	115.3048	4.2122	6.805	46.3087	3.9958
Czechia	6.8512	46.9389	2.7323	5.1385	26.4047	2.9119
Denmark	10.105	102.111	4.4315	6.8243	46.5713	3.9834
Djibouti	0	0	0		0	0
Dominica	0	0	0	0	0	0
Dominican Republic	12.6183	159.2206	5.3687	5.3812	28.9569	4.1157
Ecuador	5.7229	32.7513	2.4758	3.9822	15.8582	2.3963
Egypt	6.8698	47.1942	4.7907	5.1174	26.188	4.015
El Salvador	10.4495	109.1914	3.653	2.358	5.5603	2.2743
Equatorial Guinea	10.323	106.5634	4.7069	12.9413	167.4777	5.6865
Estonia	9.6458	93.0424	3.7614	15.7026	246.5723	5.7316
Eswatini	11.5948	134.4386	6.2858	14.3755	206.6537	6.7783
Ethiopia	13.1243	172.2469	7.2049	16.5128	272.6729	8.1253
Faroe Islands	0	0	0	0	0	0
Fiji	14.9577	223.7334	7.9468	9.792	95.8828	6.61
Finland	5.2825	27.9046	2.1186	2.4099	5.8076	1.7092
France	1.1711	1.3714	0.6354	1.4494	2.1007	0.8726
French Guiana	0	0	0	0	0	0
French Polynesia	0	0	0	0	0	0
Gabon	6.2507	39.0707	3.2634	11.2189	125.8636	4.6094
Gambia	9.9696	99.3936	5.6935	8.2451	67.9817	4.8419
Georgia	12.4274	154.4396	5.5388	4.3531	18.9494	3.3823
Germany	1.6134	2.6031	1.0412	1.5203	2.3113	2.3113
Ghana	8.8601	78.5015	5.8293	17.6815	312.6347	8.4393
Gibraltar	0	0	0	0	0	0
Greece	5.5339	30.6236	2.4596	14.0572	197.6036	4.6971
Greenland	0	0	0	0	0	0
Grenada	5.9433	35.3233	3.6672	8.6918	75.5475	4.3353
Guadeloupe	4.5099	20.3389	2.0812	1.7321	3.0003	1.3416
Guam	0	0	0	0	0	0

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Guatemala	10.0255	100.5112	4.9873	4.5187	20.4187	3.2909
Guernsey	0	0	0	0	0	0
Guinea	8.7292	76.1994	4.9657	8.9506	80.1132	5.006
Guinea-Bissau	11.9285	142.2889	4.4322	8.488	72.0512	4.0859
Guyana	2.8462	8.1007	1.3192	1.1068	1.2251	1.0212
Haiti	7.169	51.3949	3.4521	2.2058	4.8655	2.136
Honduras	9.5497	91.1969	5.1703	7.8877	62.2158	5.1749
Hong Kong	7.5697	57.3006	3.9035	6.4165	41.1715	3.5521
Hungary	5.3615	28.7455	2.9516	10.839	117.4837	4.988
Iceland	6.1778	38.1655	3.0443	20.0922	403.6946	6.2659
India	1.3647	1.8625	0.7525	0.7327	0.5368	0.5564
Indonesia	1.0416	1.085	0.7564	0.88	0.7743	0.7189
Iran	5.8074	33.7257	2.8256	4.2489	18.0528	2.6769
Iraq	13.019	169.4941	7.7934	9.1199	83.1722	6.6574
Ireland	1.022	1.0444	0.4302	1.319	1.7398	0.5476
Isle of Man	0	0	0	0	0	0
Israel	8.1316	66.1237	5.1369	12.9617	168.0064	7.0347
Italy	3.1791	10.1064	1.6558	2.0621	4.2523	1.433
Jamaica	4.3067	18.5479	2.5403	7.1705	51.4166	3.1201
Japan	8.6611	75.0151	4.0985	9.7806	95.6608	4.3546
Jersey	0	0	0	0	0	0
Jordan	3.8336	14.6967	1.9276	8.9228	79.616	3.7557
Kazakhstan	0	0	0	0	0	0
Kenya	6.2116	38.5844	3.3232	11.6125	134.8494	5.2644
Kosovo	5.8571	34.3056	2.3665	6.9648	48.5085	3.1255
Kuwait	10.7792	116.1902	6.1713	27.6976	767.1596	13.8547
Kyrgyzstan	0	0	0	0	0	0
Laos	0	0	0	0	0	0
Latvia	9.0329	81.5935	4.0577	15.363	236.0222	4.8141
Lebanon	11.8732	140.9722	5.5145	5.7114	32.6202	3.8723
Lesotho	7.8351	61.3887	5.0121	19.4631	378.8121	9.5002
Liberia	8.8601	78.502	4.7636	13.7897	190.1569	7.7805
Libya	7.2756	52.9345	4.8078	10.27	105.4736	5.4583
Liechtenstein	0	0	0	0	0	0
Lithuania	9.4687	89.6554	3.6307	4.7039	22.1269	2.4119
Luxembourg	5.4328	29.5153	2.0352	19.7734	390.9885	8.0012
Macao	10.3247	106.5986	4.4586	5.4317	29.5037	3.4083
Madagascar	8.1859	67.0095	3.0837	17.8244	317.7098	5.9622
Malawi	9.475	89.7765	3.9896	12.203	148.9136	4.5393
Malaysia	3.2457	10.5344	2.1438	3.4703	12.0428	2.018
Maldives	9.0192	81.3456	3.7675	19.1721	367.5694	7.3871
Mali	6.9092	47.7376	3.441	13.9836	195.5414	7.0168
Malta	9.4541	89.3806	4.5121	3.9692	15.7546	3.1479
Martinique	8.9073	79.3393	4.2866	21.8366	476.8377	10.2019

Mauritania	13.8648	192.2316	7.3301	8.6391	74.6336	6.0727
Mauritius	8.7301	76.2139	3.9971	19.6992	388.0597	9.2592
Mexico	2.7721	7.6848	1.1133	1.1494	1.321	0.7958
Moldova	0	0	0	0	0	0
Mongolia	5.6577	32.0097	2.1858	3.2	10.2402	1.7923
Montenegro	9.6568	93.2531	2.8187	6.145	37.7609	2.7985
Morocco	13.3511	178.2515	7.0624	11.0452	121.9971	5.9386
Mozambique	8.3459	69.6548	2.3825	5.9153	34.9914	2.6254
Myanmar (Burma)	2.7862	7.7632	1.6896	1.6621	2.7626	1.3676
Namibia	8.8703	78.6822	4.1666	16.1122	259.6045	5.3507
Nepal	12.7623	162.8764	6.2004	3.956	15.6502	3.4753
Netherlands	10.9354	119.582	4.1819	7.2466	52.513	4.3334
New Caledonia	0	0	0	0	0	0
New Zealand	5.3017	28.1082	2.6547	6.0864	37.0443	2.6479
Nicaragua	2.0237	4.0952	0.976	1.2777	1.6325	0.8717
Niger	3.9517	15.6159	2.3765	16.9702	287.9891	5.9528
Nigeria	7.3737	54.371	3.9092	6.8294	46.6407	3.2942
North Macedonia	10.1685	103.3987	3.4865	3.0711	9.4314	2.3936
Northern Mariana Islands	0	0	0	0	0	0
Norway	6.2307	38.8211	3.1065	3.4664	12.0158	2.4974
Oman	8.5704	73.451	5.2916	20.3843	415.5193	8.2069
Pakistan	6.5964	43.5123	3.1347	4.3147	18.6169	2.693
Palestine	0	0	0	0	0	0
Panama	7.9751	63.6014	4.062	6.3065	39.7718	3.3684
Papua New Guinea	0	0	0	0	0	0
Paraguay	10.0941	101.8901	3.8105	7.7531	60.1103	4.1264
Peru	8.3073	69.0105	3.7563	2.2829	5.2117	2.1975
Philippines	0.9395	0.8827	0.5583	1.7197	2.9573	0.716
Poland	3.8525	14.8416	2.1698	4.8759	23.774	2.8208
Portugal	11.0247	121.5435	4.7544	9.3369	87.177	4.4406
Puerto Rico	10.9783	120.5236	4.8751	3.6483	13.3099	3.5062
Qatar	11.8303	139.9554	6.1867	22.1425	490.2905	9.8335
Réunion	9.4096	88.5414	3.8012	8.316	69.1552	4.3294
Romania	3.64	13.2498	2.1245	6.4228	41.2524	2.6677
Russia	2.6839	7.2032	1.3379	1.3486	1.8187	1.0539
Rwanda	13.5939	184.7951	5.4912	14.0024	196.066	7.3586
Samoa	0	0		0	0	0
San Marino	0	0	0	0	0	0
Saudi Arabia	9.7894	95.8327	6.1933	7.8526	61.6632	5.6638
Senegal	11.5231	132.7812	5.6435	4.8321	23.3488	4.1911
Serbia	7.611	57.927	2.9919	17.0023	289.0791	5.6237
Seychelles	9.7918	95.8801	5.3783	11.0476	122.0504	6.0669
Sierra Leone	11.3299	128.3673	4.4383	12.7055	161.4305	5.8939

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Singapore	3.3178	11.0079	1.6058	4.6327	21.4623	2.1795
Sint Maarten	0	0	0	0	0	0
Slovakia	13.6908	187.4372	6.9251	10.8927	118.6518	6.2567
Slovenia	11.0111	121.245	4.6098	16.2637	264.5094	7.3231
Solomon Islands	0	0	0	0	0	0
Somalia	5.5604	30.9179	3.0668	18.3508	336.7535	7.4377
South Africa	3.3346	11.1196	2.3929	7.63	58.2163	3.674
South Korea	6.9248	47.9534	4.1089	6.3652	40.5161	4.3734
South Sudan	12.0022	144.0526	5.4966	10.1429	102.8774	6.1574
Spain	1.9102	3.6489	0.9706	1.5247	2.3247	0.991
Sri Lanka	14.6585	214.872	7.5076	9.0582	82.0501	5.1946
St. Barthélemy	0	0	0	0	0	0
St. Helena	15.9633	254.8255	11.5785	14.6825	215.5751	10.5333
St. Kitts & Nevis	0	0	0	0	0	0
St. Lucia	4.7856	22.9015	2.1552	16.1445	260.6449	4.5544
St. Martin	0	0	0	0	0	0
St. Pierre & Miquelon	0	0	0	0	0	0
St. Vincent & Grenadines	5.2222	27.2719	1.8175	2.3939	5.7306	1.4965
Sudan	14.5817	212.6251	8.5627	10.8392	117.4878	8.11
Suriname	0	0	0	0	0	0
Sweden	11.6771	136.355	4.8831	7.5428	56.8932	3.8568
Switzerland	10.4482	109.1649	4.191	10.3482	107.0847	3.9763
Syria	0	0	0	0	0	0
Taiwan	8.8644	78.5776	5.0119	3.2031	10.2601	3.1236
Tajikistan	0	0	0	0	0	0
Tanzania	14.1549	200.3618	5.935	19.8001	392.0455	9.7499
Thailand	1.9054	3.6305	1.0064	1.9381	3.7561	1.0714
Timor-Leste	0	0	0	0	0	0
Togo	10.8943	118.6865	5.5198	18.8062	353.675	8.7223
Trinidad & Tobago	7.7539	60.1228	3.7991	23.8618	569.3841	10.0506
Tunisia	13.1773	173.6403	6.5249	16.0612	257.9623	6.6638
Türkiye	1.4536	2.1131	0.8458	1.9669	3.8686	0.9816
Turkmenistan	0	0	0	0	0	0
Turks & Caicos Islands	0	0	0	0	0	0
U.S. Virgin Islands	0	0	0	0	0	0
Uganda	11.888	141.3237	6.5723	20.396	415.9966	9.0454
Ukraine	5.6833	32.3001	2.9119	4.5614	20.806	2.7815
United Arab Emirates	10.7911	116.4471	6.5811	8.1413	66.2805	5.1778
United Kingdom	0.5346	0.2858	0.3984	0.7138	0.5095	0.379
Uruguay	11.8371	140.1164	4.9007	7.7883	60.6579	4.3273
USA	2.082	4.3347	1.0967	0.7681	0.59	0.6998
Uzbekistan	10.5539	111.384	3.6693	6.5989	43.5455	3.4136
Vanuatu	0	0	0	0	0	0

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Venezuela	6.7539	45.6146	2.3677	4.2025	17.6609	2.055
Vietnam	1.4709	2.1637	0.8434	1.1411	1.3021	0.7516
Western Sahara	0	0	0	0	0	0
Yemen	0	0	0	0	0	0
Zambia	9.7314	94.6992	5.5258	9.9891	99.782	5.2326
Zimbabwe	8.7034	75.7499	4.6912	9.7996	96.0318	5.0848

It is worth mentioning here that for multiple regions the search interests related to MVD were constant during this 7-day period. So, for those regions, the RMSE, MSE, and MAE are reported to be 0 in Tables 2, 3, and 4. The performance metrics reported in Tables 2, 3, and 4, allow comparisons of the performance of the time series forecasting models (ARIMA, Autocorrelation, and LSTM) which were developed and implemented on the dataset using Algorithms 1, 2, and 3, respectively. These performance metrics reveal that there wasn't any particular time series forecasting model that always outperformed the other two models for every region. However, the results presented in Tables 2, 3, and 4 serve as a framework for the identification of the optimal time series forecasting model for predicting MVD virus-related web behavior in different regions. For instance, for the United States, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 0.46291, 0.805232, and 0.7681, respectively. So, based on the same, it can be concluded that the ARIMA model (Algorithm 1) is best suited to forecast web behavior related to MVD emerging from the United States. Similarly, for Canada, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 0.845154, 0.932133, and 1.1596. So, based on the same, it can once again be concluded that the ARIMA model (Algorithm 1) is best suited to forecast web behavior related to MVD emerging from Canada. However, for China, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 10.89779, 11.35232, and 8.1723. So, based on the same, it can be concluded that the LSTM model (Algorithm 3) is best suited to forecast web behavior related to MVD emerging from China. In a similar manner, an optimal model for performing forecasting of MVD-related web behavior can be deduced for each region out of all the 216 regions listed in Table 1, based on analysis of the findings presented in Tables 2–4.

Thereafter, the results of correlation analysis are presented. As shown in Figure 3, two types of correlations were investigated. First, the correlation between search interests related to MVD and search interests related to zombies (in the context of MVD-related conspiracy theory) stated as Model 1 in Figure 3, was investigated. Second, the correlation between the zombie-related search interests (in the context of MVD-related conspiracy theory) in the United States and other regions, stated as Model 2 in Figure 3, was investigated. The results of applying Model 1 on the master dataset are shown in Table 5.

Table 5. Results of correlation analysis between search interests related to MVD and search interests related to zombies (in the context of MVD-related conspiracy theory) in 216 regions.

Region Name	Pearsons r value	Pearsons p-value	Nature of correlation
Afghanistan	no correlation	no correlation	not significant
Åland Islands	no correlation	no correlation	not significant
Albania	-0.090702335	0.673391	not significant
Algeria	0.063822565	0.767019	not significant
American Samoa	no correlation	no correlation	not significant
Andorra	no correlation	no correlation	not significant
Angola	-0.100306446	0.640968	not significant
Antigua & Barbuda	-0.149116075	0.486791	not significant
Argentina	0.600519482	0.001917	statistically significant
Armenia	no correlation	no correlation	not significant
Aruba	no correlation	no correlation	not significant

Australia	0.292544706	0.165371	not significant
Austria	0.120643913	0.574431	not significant
Azerbaijan	-0.195744703	0.359316	not significant
Bahamas	0.125273682	0.559721	not significant
Bahrain	-0.012787181	0.952711	not significant
Bangladesh	-0.35785392	0.085994	not significant
Barbados	0.00500911	0.981467	not significant
Belarus	no correlation	no correlation	not significant
Belgium	0.398859048	0.053522	not significant
Belize	-0.056937592	0.79158	not significant
Benin	-0.104711124	0.626304	not significant
Bermuda	no correlation	no correlation	not significant
Bhutan	0.926431913	8.35E-11	statistically significant
Bolivia	0.052467553	0.807631	not significant
Bosnia & Herzegovina	-0.129338946	0.546946	not significant
Botswana	-0.088522736	0.680831	not significant
Brazil	-0.094590223	0.660194	not significant
British Virgin Islands	no correlation	no correlation	not significant
Brunei	0.100533352	0.640209	not significant
Bulgaria	-0.182949839	0.392176	not significant
Burkina Faso	-0.032792753	0.879096	not significant
Burundi	0.7706899	1.05E-05	statistically significant
Cambodia	0.179998984	0.399988	not significant
Cameroon	-0.159382001	0.456936	not significant
Canada	-0.082672028	0.700944	not significant
Cape Verde	-0.108891312	0.612513	not significant
Cayman Islands	-0.127280178	0.553399	not significant
Chad	-0.112659974	0.600189	not significant
Chile	-0.16714496	0.435013	not significant
China	-0.09808207	0.648424	not significant
Colombia	-0.087660028	0.683784	not significant
Comoros	0.138615038	0.518311	not significant
Congo - Brazzaville	0.043158214	0.841295	not significant
Congo - Kinshasa	-0.108070629	0.615211	not significant
Costa Rica	0.159105556	0.457727	not significant
Côte d'Ivoire	0.008714964	0.967762	not significant
Croatia	-0.23280304	0.27363	not significant
Cuba	-0.205104729	0.336332	not significant
Curaçao	no correlation	no correlation	not significant
Cyrpus	-0.096785209	0.652786	not significant
Czechia	0.149096414	0.486849	not significant
Denmark	0.075805761	0.724799	not significant
Djibouti	no correlation	no correlation	not significant
Dominica	no correlation	no correlation	not significant
Dominican Republic	-0.245334391	0.247889	not significant
Ecuador	-0.109050224	0.611992	not significant
Egypt	-0.213337626	0.316862	not significant

El Salvador	-0.042349142	0.844235	not significant
Equatorial Guinea	-0.218142785	0.305823	not significant
Estonia	-0.075414291	0.726166	not significant
Eswatini	0.279329839	0.18621	not significant
Ethiopia	-0.031797057	0.882742	not significant
Faroe Islands	no correlation	no correlation	not significant
Fiji	-0.121750998	0.570898	not significant
Finland	0.209053889	0.326905	not significant
France	0.668053741	0.00036	statistically significant
French Guiana	no correlation	no correlation	not significant
French Polynesia	no correlation	no correlation	not significant
Gabon	0.095426878	0.657366	not significant
Gambia	-0.171380952	0.423293	not significant
Georgia	0.362478283	0.08173	not significant
Germany	-0.010345017	0.961736	not significant
Ghana	0.414314395	0.044129	statistically significant
Gibraltar	no correlation	no correlation	not significant
Greece	-0.156444286	0.46538	not significant
Greenland	no correlation	no correlation	not significant
Grenada	-0.127654746	0.552222	not significant
Guadeloupe	-0.111315525	0.604574	not significant
Guam	no correlation	no correlation	not significant
Guatemala	-0.153540723	0.473804	not significant
Guernsey	no correlation	no correlation	not significant
Guinea	-0.088577053	0.680645	not significant
Guinea-Bissau	no correlation	no correlation	not significant
Guyana	-0.075872122	0.724567	not significant
Haiti	-0.036662844	0.864948	not significant
Honduras	-0.10367876	0.629729	not significant
Hong Kong	-0.292628068	0.165245	not significant
Hungary	0.066502821	0.757515	not significant
Iceland	-0.134859125	0.529818	not significant
India	0.112910195	0.599374	not significant
Indonesia	-0.132631908	0.536698	not significant
Iran	0.255540055	0.228129	not significant
Iraq	-0.317866272	0.130111	not significant
Ireland	3.47E-18	1	not significant
Isle of Man	no correlation	no correlation	not significant
Israel	0.094336362	0.661052	not significant
Italy	0.20022065	0.348213	not significant
Jamaica	0.257952873	0.223615	not significant
Japan	-0.029859044	0.889845	not significant
Jersey	no correlation	no correlation	not significant
Jordan	-0.103746534	0.629504	not significant
Kazakhstan	no correlation	no correlation	not significant
Kenya	0.004281525	0.984159	not significant
Kosovo	-0.090909091	0.672687	not significant

Kuwait	-0.098624292	0.646603	not significant
Kyrgyzstan	no correlation	no correlation	not significant
Laos	no correlation	no correlation	not significant
Latvia	-0.082679045	0.70092	not significant
Lebanon	0.850399011	1.42E-07	statistically significant
Lesotho	0.015013135	0.944491	not significant
Liberia	-0.139923493	0.514331	not significant
Libya	-0.05606639	0.794702	not significant
Liechtenstein	no correlation	no correlation	not significant
Lithuania	-0.157291159	0.462937	not significant
Luxembourg	-0.075264917	0.726688	not significant
Macao	0.013177024	0.951271	not significant
Madagascar	0.801624529	2.49E-06	statistically significant
Malawi	-0.14378595	0.502668	not significant
Malaysia	-0.066896998	0.75612	not significant
Maldives	-0.027905873	0.897012	not significant
Mali	-0.116449557	0.587902	not significant
Malta	-0.111690871	0.603348	not significant
Martinique	-0.116775918	0.586849	not significant
Mauritania	-0.093022948	0.665502	not significant
Mauritius	-0.03932881	0.855225	not significant
Mexico	-0.083723737	0.697314	not significant
Moldova	no correlation	no correlation	not significant
Mongolia	-0.147166174	0.49257	not significant
Montenegro	-0.072167714	0.737541	not significant
Morocco	-0.046490381	0.829211	not significant
Mozambique	-0.020588279	0.923928	not significant
Myanmar (Burma)	0.870771295	3.14E-08	statistically significant
Namibia	-0.119343675	0.578592	not significant
Nepal	-0.199158241	0.35083	not significant
Netherlands	0.077685891	0.718241	not significant
New Caledonia	no correlation	no correlation	not significant
New Zealand	0.034430784	0.873103	not significant
Nicaragua	-0.147146008	0.49263	not significant
Niger	-0.104590084	0.626705	not significant
Nigeria	0.370403039	0.074795	not significant
North Macedonia	-0.166045252	0.438084	not significant
Northern Mariana Islands	no correlation	no correlation	not significant
Norway	-0.316463118	0.13191	not significant
Oman	-0.088556261	0.680716	not significant
Pakistan	-0.055013307	0.79848	not significant
Palestine	no correlation	no correlation	not significant
Panama	-0.093918925	0.662465	not significant
Papua New Guinea	no correlation	no correlation	not significant
Paraguay	-0.313893217	0.13525	not significant
Peru	0.415475269	0.04348	statistically significant
Philippines	0.215999599	0.310717	not significant

Poland	0.145549599	0.497387	not significant
Portugal	0.178016266	0.405285	not significant
Puerto Rico	0.170419543	0.425938	not significant
Qatar	-0.085169268	0.692335	not significant
Réunion	-0.161577247	0.450679	not significant
Romania	0.436293089	0.033055	statistically significant
Russia	-0.287145768	0.173678	not significant
Rwanda	-0.08690683	0.686366	not significant
Samoa	no correlation	no correlation	not significant
San Marino	no correlation	no correlation	not significant
Saudi Arabia	0.095406704	0.657434	not significant
Senegal	0.073499192	0.732869	not significant
Serbia	-0.267267654	0.206747	not significant
Seychelles	0.070774484	0.742439	not significant
Sierra Leone	-0.146647907	0.494111	not significant
Singapore	0.04074778	0.850058	not significant
Sint Maarten	no correlation	no correlation	not significant
Slovakia	-0.192522789	0.367435	not significant
Slovenia	-0.052580012	0.807226	not significant
Solomon Islands	no correlation	no correlation	not significant
Somalia	-0.098682014	0.64641	not significant
South Africa	-0.515288309	0.009968	statistically significant
South Korea	0.505629707	0.011716	statistically significant
South Sudan	-0.103285849	0.631034	not significant
Spain	-0.010395398	0.961549	not significant
Sri Lanka	-0.316011788	0.132492	not significant
St. Barthélemy	no correlation	no correlation	not significant
St. Helena	0.046822547	0.828009	not significant
St. Kitts & Nevis	no correlation	no correlation	not significant
St. Lucia	-0.059897491	0.780996	not significant
St. Martin	no correlation	no correlation	not significant
St. Pierre & Miquelon	no correlation	no correlation	not significant
St. Vincent & Grenadines	-0.199562952	0.349832	not significant
Sudan	-0.090807231	0.673034	not significant
Suriname	no correlation	no correlation	not significant
Sweden	-0.21857412	0.304843	not significant
Switzerland	-0.245401511	0.247755	not significant
Syria	no correlation	no correlation	not significant
Taiwan	-0.147082649	0.492818	not significant
Tajikistan	no correlation	no correlation	not significant
Tanzania	-0.110427608	0.607477	not significant
Thailand	0.069503569	0.746915	not significant
Timor-Leste	no correlation	no correlation	not significant
Togo	-0.109324789	0.611091	not significant
Trinidad & Tobago	-0.155064952	0.469372	not significant
Tunisia	-0.328907162	0.116573	not significant
Türkiye	-0.131694408	0.539607	not significant

Turkmenistan	no correlation	no correlation	not significant
Turks & Caicos Islands	no correlation	no correlation	not significant
U.S. Virgin Islands	no correlation	no correlation	not significant
Uganda	-0.182196864	0.394161	not significant
Ukraine	-0.338520286	0.10565	not significant
United Arab Emirates	-0.03805935	0.859852	not significant
United Kingdom	0.110722888	0.606511	not significant
Uruguay	0.632244176	0.000918	statistically significant
USA	0.780639033	6.78E-06	statistically significant
Uzbekistan	0.164119111	0.44349	not significant
Vanuatu	no correlation	no correlation	not significant
Venezuela	-0.15483844	0.47003	not significant
Vietnam	-0.192602426	0.367233	not significant
Western Sahara	no correlation	no correlation	not significant
Yemen	no correlation	no correlation	not significant
Zambia	0.033333374	0.877117	not significant
Zimbabwe	-0.135748266	0.527083	not significant

As can be seen from Table 5, the list of regions where there was a statistically significant correlation between MVD-related searches and zombie-related searches (in the context of MVD-related conspiracy theory) on Google on October 4, 2023, were Argentina, Bhutan, Burundi, France, Ghana, Lebanon, Madagascar, Myanmar (Burma), Peru, Romania, South Africa, South Korea, United States, and Uruguay. This is an interesting finding as historically zombie-related web searches on Google had no correlation with web searches on Google related to MVD. In this context, October 4, 2023, was selected as the date for investigation because the FEMA emergency alert signal was broadcast on that day and the conspiracy theory was that this signal would activate the Marburg virus in people who have been vaccinated and turn some of them into zombies. Thereafter, the second correlation model (Model 2 in Figure 3) was run on the master dataset to check for correlations between zombie-related web searches on Google in the United States and zombie-related web searches from the list of 215 remaining regions. The results of the same are shown in Table 6.

Table 6. Results of correlation analysis between search interests related to zombies (in the context of MVD-related conspiracy theory) in the United States and remaining and the remaining 215 regions.

Region Name	Pearsons r value	Pearsons p-value	Nature of correlation
Afghanistan	-0.09595	0.6556	not significant
Åland Islands	0.078697	0.714724	not significant
Albania	0.011993	0.955647	not significant
Algeria	-0.1165	0.587731	not significant
American Samoa	-0.1263	0.556475	not significant
Andorra	0.343671	0.100117	not significant
Angola	-0.04035	0.851492	not significant
Antigua & Barbuda	0.088904	0.679529	not significant
Argentina	0.382087	0.065397	not significant
Armenia	-0.16178	0.450095	not significant
Aruba	0.014382	0.946823	not significant
Australia	-0.3429	0.10093	not significant
Austria	0.046433	0.82942	not significant
Azerbaijan	-0.06898	0.748768	not significant

Bahamas	0.124811	0.561182	not significant
Bahrain	-0.01622	0.940023	not significant
Bangladesh	-0.03106	0.885457	not significant
Barbados	-0.08025	0.709316	not significant
Belarus	0.073615	0.732464	not significant
Belgium	0.034153	0.874118	not significant
Belize	-0.20214	0.343505	not significant
Benin	0.079631	0.711478	not significant
Bermuda	0.119492	0.578115	not significant
Bhutan	-0.02986	0.889843	not significant
Bolivia	0.255697	0.227834	not significant
Bosnia & Herzegovina	-0.02618	0.903345	not significant
Botswana	0.005875	0.978264	not significant
Brazil	0.367615	0.077181	not significant
British Virgin Islands	0.042156	0.844936	not significant
Brunei	-0.19561	0.359643	not significant
Bulgaria	-0.12217	0.569568	not significant
Burkina Faso	0.097461	0.650512	not significant
Burundi	0.005958	0.977956	not significant
Cambodia	0.342958	0.10087	not significant
Cameroon	0.03725	0.862805	not significant
Canada	0.466469	0.021577	statistically significant
Cape Verde	0.096654	0.653228	not significant
Cayman Islands	-0.13711	0.522906	not significant
Chad	-0.26642	0.20824	not significant
Chile	0.203786	0.339516	not significant
China	-0.2226	0.295803	not significant
Colombia	-0.04168	0.846681	not significant
Comoros	0.16589	0.438519	not significant
Congo - Brazzaville	0.039259	0.855478	not significant
Congo - Kinshasa	-0.01833	0.932257	not significant
Costa Rica	-0.04959	0.817994	not significant
Côte d'Ivoire	0.088248	0.681771	not significant
Croatia	0.090166	0.67522	not significant
Cuba	0.024516	0.909469	not significant
Curaçao	0.117277	0.585235	not significant
Cyrpus	-0.03672	0.864739	not significant
Czechia	-0.18693	0.381775	not significant
Denmark	0.207912	0.329615	not significant
Djibouti	-0.03659	0.865206	not significant
Dominica	0.014971	0.944645	not significant
Dominican Republic	-0.06974	0.74608	not significant
Ecuador	0.307463	0.143872	not significant
Egypt	0.066507	0.757499	not significant
El Salvador	-0.06432	0.765254	not significant
Equatorial Guinea	-0.18634	0.383297	not significant
Estonia	-0.00644	0.976169	not significant

Eswatini	-0.02406	0.911145	not significant
Ethiopia	0.099336	0.644216	not significant
Faroe Islands	-0.00035	0.998714	not significant
Fiji	-0.17233	0.42068	not significant
Finland	0.073906	0.731445	not significant
France	0.098315	0.647641	not significant
French Guiana	-0.05422	0.801314	not significant
French Polynesia	-0.16382	0.444329	not significant
Gabon	0.128604	0.549245	not significant
Gambia	-0.09829	0.647714	not significant
Georgia	0.062136	0.773018	not significant
Germany	0.120046	0.576343	not significant
Ghana	0.035662	0.868604	not significant
Gibraltar	0.062093	0.773169	not significant
Greece	0.091659	0.670135	not significant
Greenland	0.151738	0.479073	not significant
Grenada	-0.16569	0.439078	not significant
Guadeloupe	-0.17654	0.409241	not significant
Guam	-0.19768	0.354478	not significant
Guatemala	-0.08468	0.694017	not significant
Guernsey	0.016417	0.939308	not significant
Guinea	0.093087	0.665285	not significant
Guinea-Bissau	no correlation	no correlation	not significant
Guyana	-0.05355	0.803751	not significant
Haiti	0.097893	0.649058	not significant
Honduras	-0.0947	0.659824	not significant
Hong Kong	-0.42424	0.038813	statistically significant
Hungary	0.107359	0.617554	not significant
Iceland	0.0398	0.853508	not significant
India	0.039949	0.852966	not significant
Indonesia	-0.06099	0.777109	not significant
Iran	-0.19558	0.359735	not significant
Iraq	0.135739	0.527111	not significant
Ireland	0.051086	0.812607	not significant
Isle of Man	0.073164	0.734045	not significant
Israel	-0.09267	0.666686	not significant
Italy	0.07234	0.736935	not significant
Jamaica	0.213237	0.317096	not significant
Japan	-0.35339	0.090271	not significant
Jersey	0.16045	0.453885	not significant
Jordan	0.088905	0.679525	not significant
Kazakhstan	-0.20714	0.331451	not significant
Kenya	0.018438	0.931856	not significant
Kosovo	-0.14557	0.497324	not significant
Kuwait	0.19782	0.354143	not significant
Kyrgyzstan	-0.05025	0.815624	not significant
Laos	-0.16247	0.44816	not significant

 doi:10.20944/preprints202310.1998.v1

Latvia	0.287447	0.173207	not significant
Lebanon	0.110645	0.606766	not significant
Lesotho	0.06515	0.762308	not significant
Liberia	-0.21222	0.319458	not significant
Libya	0.08889	0.679576	not significant
Liechtenstein	-0.07501	0.727568	not significant
Lithuania	-0.11568	0.590391	not significant
Luxembourg	0.094974	0.658897	not significant
Macao	-0.05698	0.791434	not significant
Madagascar	-0.09165	0.670158	not significant
Malawi	-0.04478	0.835413	not significant
Malaysia	-0.3219	0.125036	not significant
Maldives	0.076795	0.721346	not significant
Mali	-0.08522	0.692171	not significant
Malta	-0.04598	0.831055	not significant
Martinique	-0.27954	0.185867	not significant
Mauritania	0.819754	9.51E-07	statistically significant
Mauritius	-0.03636	0.86604	not significant
Mexico	0.393424	0.057171	not significant
Moldova	-0.03068	0.886823	not significant
Mongolia	0.412104	0.045387	statistically significant
Montenegro	-0.09137	0.671121	not significant
Morocco	0.160407	0.454008	not significant
Mozambique	-0.17488	0.413754	not significant
Myanmar (Burma)	0.034417	0.873154	not significant
Namibia	0.121531	0.571599	not significant
Nepal	-0.11723	0.585373	not significant
Netherlands	0.14285	0.505484	not significant
New Caledonia	-0.2661	0.208817	not significant
New Zealand	0.124488	0.562206	not significant
Nicaragua	-0.03112	0.885239	not significant
Niger	0.156955	0.463905	not significant
Nigeria	0.217549	0.307175	not significant
North Macedonia	0.173099	0.418589	not significant
Northern Mariana Islands	0.646713	0.000638	statistically significant
Norway	0.08754	0.684195	not significant
Oman	-0.03557	0.868938	not significant
Pakistan	-0.13549	0.527882	not significant
Palestine	0.098489	0.647058	not significant
Panama	0.168015	0.432593	not significant
Papua New Guinea	-0.07654	0.722227	not significant
Paraguay	0.153044	0.475254	not significant
Peru	0.234161	0.270762	not significant
Philippines	-0.39349	0.057128	not significant
Poland	0.173083	0.418631	not significant
Portugal	0.143596	0.50324	not significant

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Puerto Rico	-0.02542	0.906154	not significant
Qatar	0.125201	0.55995	not significant
Réunion	0.054686	0.799656	not significant
Romania	0.025209	0.906921	not significant
Russia	-0.05316	0.805152	not significant
Rwanda	0.014844	0.945115	not significant
Samoa	-0.28245	0.181134	not significant
San Marino	0.060922	0.777342	not significant
Saudi Arabia	-0.03375	0.875606	not significant
Senegal	0.072302	0.737068	not significant
Serbia	-0.1206	0.574572	not significant
Seychelles	0.013748	0.949161	not significant
Sierra Leone	-0.14807	0.489887	not significant
Singapore	0.255118	0.228925	not significant
Sint Maarten	-0.12123	0.572562	not significant
Slovakia	0.048977	0.820217	not significant
Slovenia	0.127292	0.553361	not significant
Solomon Islands	0.013335	0.950688	not significant
Somalia	0.109009	0.612126	not significant
South Africa	0.052403	0.807865	not significant
South Korea	0.368282	0.076606	not significant
South Sudan	-0.18285	0.392433	not significant
Spain	0.139112	0.516797	not significant
Sri Lanka	-0.05101	0.81287	not significant
St. Barthélemy	0.071335	0.740467	not significant
St. Helena	0.001053	0.996102	not significant
St. Kitts & Nevis	-0.05172	0.810321	not significant
St. Lucia	-0.24535	0.24786	not significant
St. Martin	-0.08901	0.679155	not significant
St. Pierre & Miquelon	0.02774	0.897619	not significant
St. Vincent & Grenadines	0.132365	0.537525	not significant
Sudan	-0.11314	0.598624	not significant
Suriname	0.054396	0.800697	not significant
Sweden	0.136607	0.524449	not significant
Switzerland	0.017598	0.934952	not significant
Syria	0.015707	0.941928	not significant
Taiwan	0.4215	0.040229	statistically significant
Tajikistan	0.172028	0.421518	not significant
Tanzania	-0.1645	0.442414	not significant
Thailand	-0.01067	0.960521	not significant
Timor-Leste	0.5755	0.003256	statistically significant
Togo	0.099706	0.642978	not significant
Trinidad & Tobago	0.137748	0.520958	not significant
Tunisia	0.106702	0.619719	not significant
Türkiye	0.284156	0.178401	not significant
Turkmenistan	0.137217	0.522581	not significant

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Turks & Caicos Islands	0.319718	0.127765	not significant
U.S. Virgin Islands	0.06417	0.765787	not significant
Uganda	0.013549	0.949899	not significant
Ukraine	0.089928	0.67603	not significant
United Arab Emirates	-0.05261	0.80713	not significant
United Kingdom	0.39561	0.055681	not significant
Uruguay	0.204763	0.337156	not significant
USA	-0.42842	0.036735	statistically significant
Uzbekistan	-0.07757	0.718644	not significant
Vanuatu	0.110428	0.607474	not significant
Venezuela	0.118984	0.579746	not significant
Vietnam	0.151467	0.479867	not significant
Western Sahara	0.088108	0.68225	not significant
Yemen	0.2617	0.216722	not significant
Zambia	-0.07489	0.727997	not significant

As can be seen from Table 6, the list of regions where this correlation was statistically significant were Canada, Hong Kong, Mauritania, Mongolia, Northern Mariana Islands, Taiwan, Timor-Leste, and Uzbekistan. This is also an interesting finding as the FEMA emergency alert signal was broadcasted only in the United States. However, the results show that the zombie-related searches (in the context of MVD-related conspiracy theory) from the United States had a statistically significant correlation with zombie-related searches (in the context of MVD-related conspiracy theory) emerging from multiple other regions even though no emergency signal or similar was broadcasted in those regions. Thereafter, an analysis was also performed to determine the list of regions out of these 216 regions where there was a positive increase in zombie-related searches (in the context of MVD-related conspiracy theory) between 2 PM and 3 PM (EST) on October 4, 2023. This time range was specifically chosen for this analysis as the FEMA emergency alert signal was broadcast at 2.20 PM (EST) on October 4, 2023. The results are shown in Table 7.

Table 7. Representation of regions where there was a positive increase in zombie-related searches (in the context of MVD-related conspiracy theory) between 2 PM and 3 PM (EST) on October 4, 2023.

Region Name	**Search interest at 2 PM**	**Search interest at 3 PM**	**Percentage increase**
Algeria	6	16	166.6667
Argentina	31	39	25.80645
Austria	18	20	11.11111
Belgium	19	22	15.78947
Bolivia	10	22	120
Cambodia	22	77	250
Canada	52	58	11.53846
Costa Rica	5	10	100
Cuba	13	14	7.692308
Denmark	29	33	13.7931
Dominican Republic	4	5	25
Finland	8	9	12.5
France	23	25	8.695652
Greece	8	18	125
Guatemala	4	7	75

 doi:10.20944/preprints202310.1998.v1

Hungary	11	21	90.90909
India	64	70	9.375
Indonesia	62	66	6.451613
Israel	13	16	23.07692
Italy	32	34	6.25
Jersey	2	10	400
Lebanon	6	10	66.66667
Mexico	39	41	5.128205
Morocco	16	19	18.75
Nigeria	31	47	51.6129
Palestine	6	8	33.33333
Poland	39	46	17.94872
Portugal	12	14	16.66667
Qatar	20	23	15
Senegal	8	9	12.5
Slovenia	2	4	100
South Korea	80	87	8.75
Spain	38	41	7.894737
Sri Lanka	22	34	54.54545
Sweden	27	32	18.51852
Switzerland	11	14	27.27273
Taiwan	16	87	443.75
Tunisia	6	11	83.33333
Turks & Caicos Islands	4	7	75
Ukraine	25	28	12
United Kingdom	18	19	5.555556
United States	51	100	96.07843
Uruguay	2	8	300
Vietnam	55	62	12.72727
Zambia	11	14	27.27273

Thereafter, further analysis of the trends of search interests in regions where there was a statistically significant correlation between MVD-related web searches and zombie-related web searches (in the context of MVD-related conspiracy theory) was performed. In this analysis, the trends of zombie-related web searches (in the context of MVD-related conspiracy theory) during the entire day on October 4, 2023, were analyzed.

It is worth noting that in Figures 13 and 14, the Y-axis represents the value of search interests as obtained from Google Trends and the X-axis represents the hour, where 12.01 to 1.00 is considered hour 1, 1.01 to 2.00 is considered hour 2, and so on. From Figures 13 and 14, the trends and variations of searches in these regions can be observed. For instance, there was a peak in search interests in multiple regions between 2 PM and 3 PM. At the same time, it is interesting to note that there was a peak in search interests in Bhutan between 5 PM to 8 PM. A different pattern can be seen in Argentina, where the peak in search interests occurred between 2 AM to 5 AM. In a similar manner, these Figures can be analyzed to interpret the similarities and variations in terms of the trends in zombie-related web searches (in the context of MVD-related conspiracy theory) on October 4, 2023, in different geographic regions where there was a statistically significant correlation between MVD-related web searchers on Google and zombie-related web searches (in the context of MVD-related conspiracy theory) on Google.

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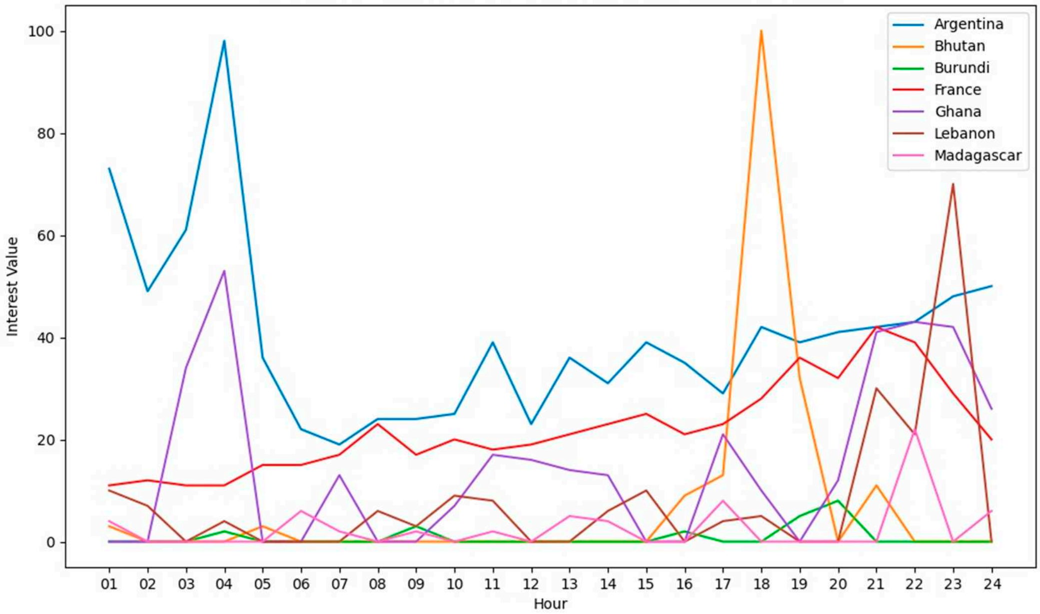

Figure 13. Trends in zombie-related web searches (in the context of MVD-related conspiracy theory) on October 4, 2023, in Argentina, Bhutan, Burundi, France, Ghana, Lebanon, Madagascar.

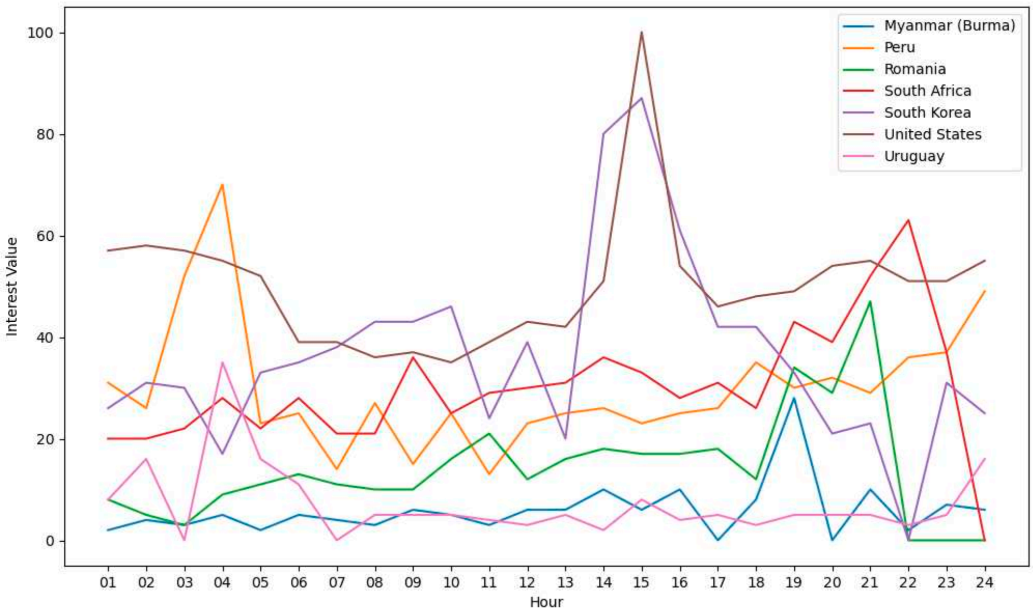

Figure 14. Trends in zombie-related web searches (in the context of MVD-related conspiracy theory) on October 4, 2023, in Myanmar (Burma), Peru, Romania, South Africa, South Korea, the United States, and Uruguay.

The research work presented and discussed in this paper has a few limitations. First, the data obtained by Google Trends is the data generated by only a certain percentage of the worldwide population who have access to the internet and opt to use Google as their primary search engine. Second, it is important to note that the data collected from Google Trends and analyzed in this work represents the relative search volumes rather than absolute values of the total amount of Google Searches emerging from different geographic regions. Finally, there is a notable inadequacy related to the disclosure of the methodology and underlying algorithms used by Google in producing search interest data.

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5. Conclusion

As a result of outbreak of the MVD in February 2023 and the high fatality rate of the same, on a global scale, people have been devoting a substantial amount of time to social media platforms and the internet in general over the last few months to acquire and disseminate information pertaining to MVD. During virus outbreaks in the recent past, such as COVID-19, Influenza, Lyme Disease, and Zika virus, researchers from different fields such as Healthcare, Epidemiology, Big Data, Data Analysis, Data Science, and Computer Science utilized Google Trends to extract and analyze multimodal components of web behavior of the general public in order to examine, explore, interpret, assess, and forecast the worldwide perception, readiness, reactions, and response linked to these virus outbreaks. During such virus outbreaks of the past, the application of time series forecasting models such as ARIMA, LSTM, and Autocorrelation to web searches to model, predict, and forecast the web behavior of the general public in the context of the outbreaks also attracted the attention of researchers from different disciplines. Furthermore, the paradigms of web behavior on the internet during virus outbreaks of the past also led to the development and dissemination of conspiracy theories that led to a range of reactions in the general public. For example, during the outbreak of COVID-19, a popular conspiracy theory was that 5G towers had a role in the transmission of the virus. The analysis of such conspiracy theories during virus outbreaks of the past has also been relevant to understanding the underlying patterns of information seeking and sharing on the internet. The outbreak of MVD and an electronic alert (for testing purposes) sent by the Federal Emergency Management Agency (FEMA) to all television, radio, and mobile devices throughout the United States on October 4, 2023, has given rise to an unconventional conspiracy theory that associates the Marburg Virus with a zombie outbreak. Specifically, the conspiracy theory was centered around the concept that the FEMA alert would activate the Marburg virus in people who have been vaccinated and turn some of them into zombies. This conspiracy theory spread like wildfire on the internet to the extent that soon after the FEMA alert signal was broadcast, Jeremy Edwards (press secretary and deputy director of public affairs at FEMA) provided a statement to the public to clarify that he was not a zombie. Due to this recent outbreak of MVD and the conspiracy theory involving the same, it is imperative to conduct an investigation into the underlying patterns of web behavior in order to get a comprehensive understanding of the paradigms of information seeking and sharing used by the general public in this particular context. No prior work in this field thus far has focused on the same. Therefore, the work presented in this paper aims to address this research gap and makes multiple scientific contributions to this field. It presents the results of performing time series forecasting of the search interests related to MVD emerging from 216 different regions on a global scale using three models - ARIMA, LSTM, and Autocorrelation. The results of this analysis in terms of RMSE, MSE, and MAE are presented and discussed. The results of this analysis present the optimal model for forecasting web behavior related to MVD in each of these regions. For instance, for the United States, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 0.46291, 0.805232, and 0.7681, respectively. So, based on the same, it can be concluded that the ARIMA model is best suited to forecast web behavior related to MVD emerging from the United States. Similarly, for Canada, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 0.845154, 0.932133, and 1.1596. So, based on the same, it can once again be concluded that the ARIMA model is best suited to forecast web behavior related to MVD emerging from Canada. However, for China, the RMSE values generated by ARIMA, Autocorrelation, and LSTM for the test set are 10.89779, 11.35232, and 8.1723. So, based on the same, it can be concluded that the LSTM model is best suited to forecast web behavior related to MVD emerging from China. The paper also presents the findings from investigating two types of web behavior for correlations. First, the correlation between search interests related to MVD and search interests related to zombies (in the context of MVD-related conspiracy theory) was investigated. Second, the correlation between zombie-related search interests (in the context of MVD-related conspiracy theory) in the United States and other regions was investigated. The findings from the first analysis show that the list of regions where there was a statistically significant correlation between MVD-related searches and zombie-related searches (in the context of MVD-related conspiracy theory) on Google on October 4, 2023, were Argentina, Bhutan, Burundi, France, Ghana, Lebanon, Madagascar, Myanmar (Burma), Peru, Romania, South Africa, South Korea, United States, and Uruguay. This is an interesting finding as historically zombie-related web searches on Google had no correlation with web searches on Google related to MVD. The findings from the second analysis show that the list of regions where this correlation was statistically significant were Canada, Hong Kong, Mauritania, Mongolia, Northern Mariana Islands, Taiwan, Timor-Leste, and Uzbekistan. This is also an interesting finding as the FEMA emergency alert signal was broadcasted only in the United States. Finally, the paper also presents an analysis of variation and degree of increase of search interests in the context of this conspiracy theory emerging from different geographic regions. As per the best knowledge of the authors, no similar work has been done in this field thus far. Future work would involve detecting and analyzing the popular topics represented in Google Searches about this conspiracy theory to interpret the specific themes of information seeking and sharing on Google in the context of this conspiracy theory.

Author Contributions: Conceptualization, N.T.; methodology, N.T., S.C, K.A.P, N.A., A.P., R.S.; software, N.T., S.C, K.A.P, A.P., R.S.; validation, N.T.; formal analysis, N.T., S.C, K.A.P, N.A., A.P., R.S.; investigation, N.T., S.C, K.A.P, A.P., R.S.; resources, N.T.; data curation, N.T.; writing—original draft preparation, N.T., C.H., V.K.; writing—review and editing, N.T.; visualization, N.T., S.C, K.A.P, A.P., R.S.; supervision, N.T.; project administration, N.T.; funding acquisition, Not Applicable. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data analyzed in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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