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Data Descriptor

Country-Specific Interests towards Fall Detection from 2004–2021: An Open Access Dataset and Research Questions

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Abstract: Falls, which are increasing at an unprecedented rate in the global elderly population, are associated with a multitude of needs such as healthcare, medical, caregiver, and economic, and they are posing various forms of burden on different countries across the world, specifically in the low- and middle-income countries. For these respective countries to anticipate, respond, address, and remedy these diverse needs either by using their existing resources, or by developing new policies and initiatives, or by seeking support from other countries or international organizations dedicated to global public health, the timely identification of these needs and their associated trends is highly necessary. This paper addresses this challenge by presenting a study that uses the potential of the modern Internet of Everything lifestyle, where relevant Google Search data originating from different geographic regions can be interpreted to understand the underlining region-specific user interests towards a specific topic, which further demonstrates the public health need towards the same. The scientific contributions of this study are two-fold. First, it presents an open-access dataset that consists of the user interests towards fall detection for all the 193 countries of the world studied from 2004–2021. In the dataset, the user interest data is available for each month for all these countries in this time range. Second, based on the analysis of potential and emerging research directions in the interrelated fields of Big Data, Data Mining, Information Retrieval, Natural Language Processing, Data Science, and Pattern Recognition, in the context of fall detection research, this paper presents 22 research questions that may be studied, evaluated, and investigated by researchers using this dataset.

Dataset: https://dx.doi.org/10.21227/85jy-7m92.

Dataset License: CC BY 4.0.

Keywords: fall detection; elderly; aging population; dataset; healthcare; public health need; search interest; Google Trends; web behavior; Google Search; Internet of Everything

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1. Background

Worldwide, the longevity of people is increasing due to advanced healthcare facilities and advances in medical research [1]. Today, most individuals may expect to survive until they are sixty or older for the first time in history. The number of elderly people across the globe is projected to reach 2 billion by the year 2050, up from 900 million in 2015. Globally, the number of individuals above the age of 80 has grown to 125 million. China alone is expected to have a population of almost 100 million by the year 2050 and 434 million individuals in the age group of 80 or above by the end of the current century. The same projection also predicts that in the year 2050, 80% of the world's elderly people would be living in low- and middle-income nations. Population aging, which has created a demographic transition in different parts of the world, began in high-income nations (such as Japan) initially, but it is currently the low- and middle-income countries that are the most affected by it. The ratio of elderly people to younger people in nations such as

Chile, China, the Islamic Republic of Iran, and Russia is predicted to be about equal to that of Japan by the middle of the century [2]. About 70% of the global elderly population, prone to falls, lives in developing countries, and this proportion is expected to increase in the upcoming decades [3].

Falls, the second leading cause of accidental deaths, are a serious issue for the rapidly increasing elderly population in different parts of the world [2,4]. According to [5], a fall is an unanticipated incident of coming down on the ground or floor triggered by a push or pull, environmental features, unconsciousness, or any similar health-related limitations or disorders. The rate of falls in the elderly has tremendously increased in the recent past and is expected to increase even more. On an annual basis, about 37.3 million fall incidents occur in the global elderly population that are associated with health-related concerns, injuries, and treatment of minor to major degrees. Globally, falls are ranked as the 18th leading cause of age-standardized rates of disability-adjusted life years, outranking chronic kidney diseases, Alzheimer's, Dementia, and asthma [6]. Falls are associated with the greatest number of deaths in elderly people in the age group of 65 years and more. Falls are the leading cause of injury-related deaths in all older adults 70 years or older [7]. Approximately 684,000 falls are associated with deaths every year [4]; 80% of such fatal falls occur in low- and middle-income nations, with regions in the Western Pacific and South-East Asia accounting for 60% of these deaths [4]. Globally, approximately 30% of the elderly experience at least 1 fall each year [8], and this percentage is predicted to rise to 42% over the next few years [9,10]. One of the major consequences of this increase of falls leads to a greater share of healthcare, medical, and caregiving costs on account of morbidity and mortality due to falls in the elderly, which is specifically increasing at a steep rate in the low- and middle-income nations. For instance, as per [11], years lived with disability associated with falls in the elderly are 631.2 per 100,000 (population) in India and 674.4 per 100,000 in China, compared with 472.2 per 100,000 in the United States. The years lived with disability due to falls in the age group of 50 to 59 years is 66% in developing countries, almost twice as high as developed countries [12].

In addition to posing a huge burden on the world economies in different parts of the world, both in low-income and high-income countries, in the form of healthcare and caregiver costs, falls can also have a multitude of behavioral, social, emotional, mental, psychological, and health-related impacts to the elderly. At a broad level, these effects from falls can be categorized as individual—injuries, bruises, blood clots; social life—reduced mobility leading to loneliness and social isolation; cognitive or mental—fear of moving around, loss of confidence in carrying out daily routine activities, and financial—the cost of medical treatment and caregivers [13].

Over the last few years, studies have shown the need and interest towards the development of fall detection systems in different high-income countries such as the United States [13], Australia [14], United Kingdom [15], Spain [16], Singapore [17], Switzerland [18], Canada [19], New Zealand [20], and Japan [21]; in upper middle income countries such as—China [22], Malaysia [23], Brazil [24], Russia [25], Ecuador [26], Thailand [27], Colombia [28], Jamaica [29], and Iraq [30]; in lower middle income group countries such as Indonesia [31], Sri Lanka [32], Iran [33], India [34], Bangladesh [35], Nigeria [36], Pakistan [37], Egypt [38], and Vietnam [39], and in low income group countries such as Malawi [40], Ethiopia [41], and Rwanda [42]. Works by researchers have also shown that rates of falls are significantly high in some of these countries. For instance, in India, the annual rate of falls in the elderly is in the range of 14% to 51% [43]. In China, Hong Kong, Singapore, and Macao, the rate of falls in the elderly is in the range of 14.7% to 34% [44], and in Korea, the rate is 15.9% to 25.1% [45]. Fall detection and prevention are not given due importance in several countries due to the lack of timely identification of the associated needs with supporting evidence demonstrating these needs [46]. Several recent studies indicate that governments from different countries all over the world, specifically from the low- and middle-income countries, urgently need data, evidence, and facts associated with fall-related needs in the elderly to develop and integrate fall detection, fall prevention, and associated response and remedial measures, policies, and initiatives related to falls [47–50].

For the above-mentioned country-specific classification of fall detection-related studies, we followed the categorization system of the World Bank [51] who categorize countries as high-income, upper middle income, lower middle income, and low-income group, based on the gross national income per capita. While these works [13–42] investigated the needs and associated interest towards fall detection systems and applications for the elderly, but the methodologies applied for investigation and gauging these needs were highly diverse that included various forms of surveys, user responses, opinion polls, user research, market surveys, market research, qualitative, and quantitative methods, just to name a few; therefore, these needs from these works cannot be evaluated on the same scale and compared.

Because of the increasing and varying rate of falls in the elderly in different geographic regions of the world, which has minor to major implications and consequences on the economies of the respective countries, it is the need of the hour to conduct a study that identifies and investigates these country-specific needs related to fall detection in the elderly by using the same methodology for all the countries of the world. Such a study would be helpful for these respective countries to channelize their available resources to anticipate, respond, address, and remedy these diverse needs, or to develop new policies and initiatives based on the increasing or decreasing trends associated with such needs, or to seek support from other countries or international organizations dedicated to global public health such as World Health Organization or United Nations. Addressing this research challenge by conducting such a comprehensive study that presents the country-specific needs and interests related to fall detection in the form of an open-access dataset and discusses potential research questions that may be investigated or evaluated by using this dataset serves as the main motivation for this work.

The first step towards developing such a dataset that investigates these needs at a country-level for all the 193 countries of the world [52] by using the same methodology involves identifying the methodology that can be applied to study the fall detection needs-related data in each of these countries. With the advent of the Internet of Everything lifestyle [53], in recent times, people's everyday lives involve interacting with computers and a myriad of technology-based gadgets and devices in multiple ways while using various forms of Internet-based services and applications [54]. The use of the internet, powered by the search engine industry that it supports, is now common across the globe. For instance, Google now processes about 3.5 billion searches per day and about 1.2 trillion searches per year [55]. Google accounts for an overwhelming majority of global internet searches as compared to all its competitors [56]. For instance, in countries such as India, Brazil, Spain, Italy, and Hong Kong, Google accounts for 95.45%, 92.58%, 91.97%, 91.34%, and 91.12% of all the internet searches, respectively [57]. The analysis of online search data has been of interest to researchers studying web behavior [58,59]. For instance, the study of web behavior towards a specific technology indicates user interests in that technology [60,61], which serves as an indicator of the overall public health need for that technology [62]. The public interests analyzed from web behavior data towards a specific technology could also serve as a good indicator of the market potential, for example, its sales outlook, consumer acceptance, the use and applicability of the technology, as well as the general trends of the topic of interest [61]. The degree of interest of the net citizens towards technology can carry a great deal of information, which can be used to influence many businesses, political, economic, social, and governmental policy-making decisions. There can be many such use cases of studying and interpreting search interests and web behavior on Google; we will discuss one here, with a specific focus on customer search behavior. Potential customers of a product always aim to maximize their satisfaction by reducing any uncertainties, be it psychological or financial, and avoid risks involved in the purchasing process [63]. This prompts them to engage in information-seeking behavior via the internet, which quite often leads to the customer making an online purchase [64] as there is a positive correlation between one's willingness to search the internet and purchasing a product online [65].

While individuals can search for anything online, ranging from gadgets, products, jobs, goods, and services, just to name a few, recent studies have shown that 80% of internet users in the US have searched for a health-related topic or healthcare-related needs online [66,67]. The most popular tool for analyzing such web-based behavior based on Google Search data is Google Trends [68]. Google Trends is a website by Google that provides users a means to obtain global web behavior data [68]. Google Trends has three major advantages over traditional surveys: (1) there is no cost involved in studying and surveying the search data, whereas traditional surveys are quite often associated with costs; (2) conducting surveys regularly on a diverse global user group is very difficult whereas Google Trends considers the global search data from daily search results on Google, that can be studied and analyzed easily [69], and (3) the data from Google Trends can be easily mined and analyzed without any delay, but traditional surveys might incur time delays based on the recruitment and inclusion criteria of participants [70].

Google Trends data has been of significant interest to healthcare researchers, and recent studies have shown that Google Trends data can be studied and interpreted for infectious outbreaks and diseases such as Influenza [71], Lyme Disease [72], various tropical diseases in India [73], Syphilis [74], HIV [75], and Zika virus [76]. Google Trends has also been used to forecast economic indicators [77] and financial markets [78], as well as analysis of Google Trends data was used to detect regional flu outbreaks before the conventional monitoring systems came into practice [79]. Google Trends is increasingly used in different studies, with the number of research articles related to Google Trends growing over 50% per year [80]. So, the use of Google Trends to investigate the interest and associated need related to falls in the elderly, which can have health-related concerns of varying degrees and affects different economies of the world in different ways, seems to hold high potential and shows promise for investigation.

Therefore, for the development of this dataset and the associated research questions, we used Google Trends and studied the relevant web behavior data, which originated from all the countries of the world [52] from 2004 to 2021, by exploring and integrating the latest advancements from the fields of Big Data, Data Mining, Information Retrieval, Natural Language Processing, Data Science, and Pattern Recognition. The rest of this paper is organized as follows. In Section 2, we present the description and a brief analysis of this dataset. The methodology that we used to develop this dataset is presented in Section 3. Section 4 presents 22 research questions based on potential and emerging research directions in this field for researchers to study, evaluate, and investigate using this dataset. Section 5 concludes the paper by summarizing the contributions of this study and discussing the scope for future work.

2. Data Description and Analysis

This section describes and presents a brief analysis of the dataset. The dataset is publicly available at https://dx.doi.org/10.21227/85jy-7m92, which we developed by mining the relevant web behavior from all the 193 countries [52] of the world from 2004–2021. The dataset consists of the monthly user interests related to fall detection, in this time range, for each of these countries. In the dataset that consists of 1 comma-separated values (.csv) file, there are a total of 194 columns, with the first column being the month and the remaining 193 columns representing each of these 193 countries in alphabetical order. An overview of these attributes of the dataset, along with their associated characteristics, is shown in Table 1. For clarity of representation, all the attributes have not been represented in this Table. As can be seen from Table 1, the data type of the first attribute, Month, is of "date" type. All the other 193 attributes are of "numerical" type, with 0 being the minimum possible value and 100 being the maximum possible value of these respective attributes. While various organizations and associations define or do not define a certain geographic region as a country, we decided to follow a globally accepted definition, so we conducted the study for the development of this dataset on those geographic regions which are defined as countries by the United Nations and who are members of the same [52]. This definition of countries by the United Nations also includes the high-income, upper-middle-income, lower-middle-income, and low-income group countries. These countries [52] are shown in Table 2.

Table 1. Overview of the different attributes of the dataset and their associated characteristics.

Attribute Name	Characteristics	Range	Datatype
Month	Each month from 2004 to 2021	January 2004–June 2021	Date
Afghanistan	Represents Search Interest data for Afghanistan	0–100	Numerical
Albania	Represents Search Interest data for Albania	0–100	Numerical
Algeria	Represents Search Interest data for Algeria	0–100	Numerical
.	.	.	.
.	.	.	.
.	.	.	.
Vietnam	Represents Search Interest data for Vietnam	0–100	Numerical
Yemen	Represents Search Interest data for Yemen	0–100	Numerical
Zambia	Represents Search Interest data for Zambia	0–100	Numerical
Zimbabwe	Represents Search Interest data for Zimbabwe	0–100	Numerical

Table 2. The list of 193 countries of the world as per United Nations for each of which we evaluated the user interests related to fall detection from 2004–2021.

List of Countries as per United Nations			
Afghanistan	Djibouti	Libya	Saint Vincent and the Grenadines
Albania	Dominica	Liechtenstein	Samoa
Algeria	Dominican Republic	Lithuania	San Marino
Andorra	Ecuador	Luxembourg	Sao Tome and Principe
Angola	Egypt	Madagascar	Saudi Arabia
Antigua and Barbuda	El Salvador	Malawi	Senegal
Argentina	Equatorial Guinea	Malaysia	Serbia
Armenia	Eritrea	Maldives	Seychelles
Australia	Estonia	Mali	Sierra Leone
Austria	Ethiopia	Malta	Singapore
Azerbaijan	Fiji	Marshall Islands	Slovakia
Bahamas	Finland	Mauritania	Slovenia
Bahrain	France	Mauritius	Solomon Islands
Bangladesh	Gabon	Mexico	Somalia
Barbados	The Gambia	Micronesia (the Federated States of)	South Africa
Belarus	Georgia	Monaco	South Sudan
Belgium	Germany	Mongolia	Spain
Belize	Ghana	Montenegro	Sri Lanka
Benin	Greece	Morocco	Sudan
Bhutan	Grenada	Mozambique	Suriname
Bolivia	Guatemala	Myanmar	Swaziland
Bosnia and Herzegovina	Guinea	Namibia	Switzerland
Botswana	Guinea-Bissau	Nauru	Sweden
Brazil	Guyana	Nepal	Syria
Brunei Darussalam	Haiti	Netherlands	Tajikistan
Bulgaria	Honduras	New Zealand	Thailand
Burkina Faso	Hungary	Nicaragua	The former Yugoslav Republic of Macedonia
Burundi	Iceland	Niger	Timor Leste
Cambodia	India	Nigeria	Togo
Cameroon	Indonesia	Norway	Tonga
Canada	Iran	Oman	Trinidad and Tobago
Cape Verde	Iraq	Pakistan	Tunisia
Central African Republic	Ireland	Palau	Turkey

Table 2. *Cont.*

List of Countries as per United Nations			
Chad	Israel	Panama	Turkmenistan
Chile	Italy	Papua New Guinea	Tuvalu
China	Jamaica	Paraguay	Uganda
Colombia	Japan	Peru	Ukraine
Comoros	Jordan	Philippines	United Arab Emirates
Congo (Republic of the)	Kazakhstan	Poland	United Kingdom
Costa Rica	Kenya	Portugal	United of Republic of Tanzania
Côte d'Ivoire	Kiribati	Qatar	United States
Croatia	Kuwait	Republic of Korea	Uruguay
Cuba	Kyrgyzstan	Republic of Moldova	Uzbekistan
Cyprus	Lao People's Democratic Republic	Romania	Vanuatu
Czech Republic	Latvia	Russian Federation	Venezuela
Democratic People's Republic of Korea	Lebanon	Rwanda	Vietnam
Democratic Republic of the Congo	Lesotho	Saint Kitts and Nevis	Yemen
Denmark	Liberia	Saint Lucia	Zambia

While conducting the study using Google Trends, which is described in detail in Section 3, we mined the countrywide interests related to fall detection for each month starting from 2004 to 2021. The earliest month being January 2004, and the most recent month (at the time of conducting this study) for which we were able to mine a search interest value was June 2021. We could not include any search interest data from prior to 2004 as the oldest data related to search interests available on Google Trends is from January 2004. In the dataset, each row represents a month and the associated country-level search interests related to fall detection for that specific month are present in different columns. There are a total of 211 rows in the dataset where the first row is the column header, and the remaining rows represent each month in the range of January 2004 to June 2021. The search interest in the dataset is a numerical value in the range of 0 to 100, where 0 represents minimal or no search interest and 100 represents peak interest. This scale of representing search interests in the range of 0 to 100 was chosen because Google Trends [68] also follows the same scale. These interest values are computed by using Google Trends by mining and studying the relevant web behavior based on Google Search data. Google Trends data [81] reflects searches people make on Google every day, but it can also reflect irregular search activity, such as automated searches or other queries. Google Trends filters out some types of searches, such as:

i. Searches made by very few people: Trends only show data for popular terms, so search terms with low volume appear as "0".
ii. Duplicate searches: Trends eliminates repeated searches from the same person over a short period of time.
iii. Special characters: Trends filters out queries with apostrophes and other special characters.

Google Trends uses an unfiltered sample of the actual Google Search data for computing search interests related to a topic or topics. The associated data is anonymized, categorized, and aggregated. Google Trends [81] normalizes the data used in a study by the following process:

i. It divides each data point by the total searches of the geography and time range it represents to compare relative popularity.
ii. If the division cannot be performed due to insufficient data, places with greater search volumes are ranked higher.

iii. It scales the resulting numbers on a range of 0 to 100 depending on the ratio of searches related to the topic under consideration as compared to the searches related to all other topics.
iv. The search interest for two or more regions might not always reflect the total volume of searches coming from those regions.

For our study, the topic was fall detection. There were some countries from which, during certain months, not enough relevant web behavior data was available for Google Trends to compute a score for deducing the search interest related to fall detection. Such a situation represents minimal or no search interest related to fall detection from those countries during those specific months. To represent the same, we assigned a 0 value for those specific months in the columns of these respective countries. The search interest-based data of this dataset can be studied by visualization, analysis, and interpretation of the increasing and decreasing trends in user interests in the high-income, upper middle income, lower middle income, and low-income group countries for each month since 2004. We present this visualization for some of the countries (randomly selected) from this dataset in Figures 1–3. While we could have represented all these countries and their varying trends in user interests in one figure but for clarity of representation of the associated trends and patterns in the search interest values, we have represented this data using different figures for select few countries.

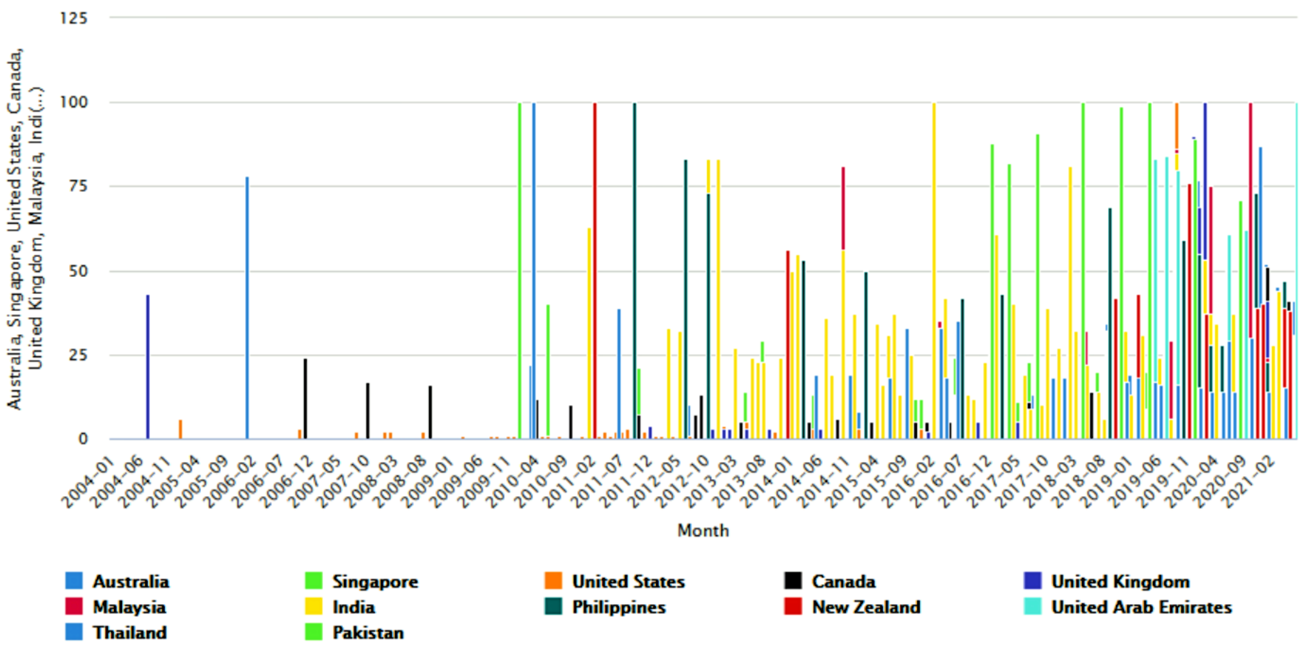

Figure 1. Data visualization that shows the varying patterns of interests related to fall detection from 2004–2021 for the countries—Singapore, Australia, United States, Canada, United Kingdom, Malaysia, India, Philippines, New Zealand, United Arab Emirates, Thailand, and Pakistan.

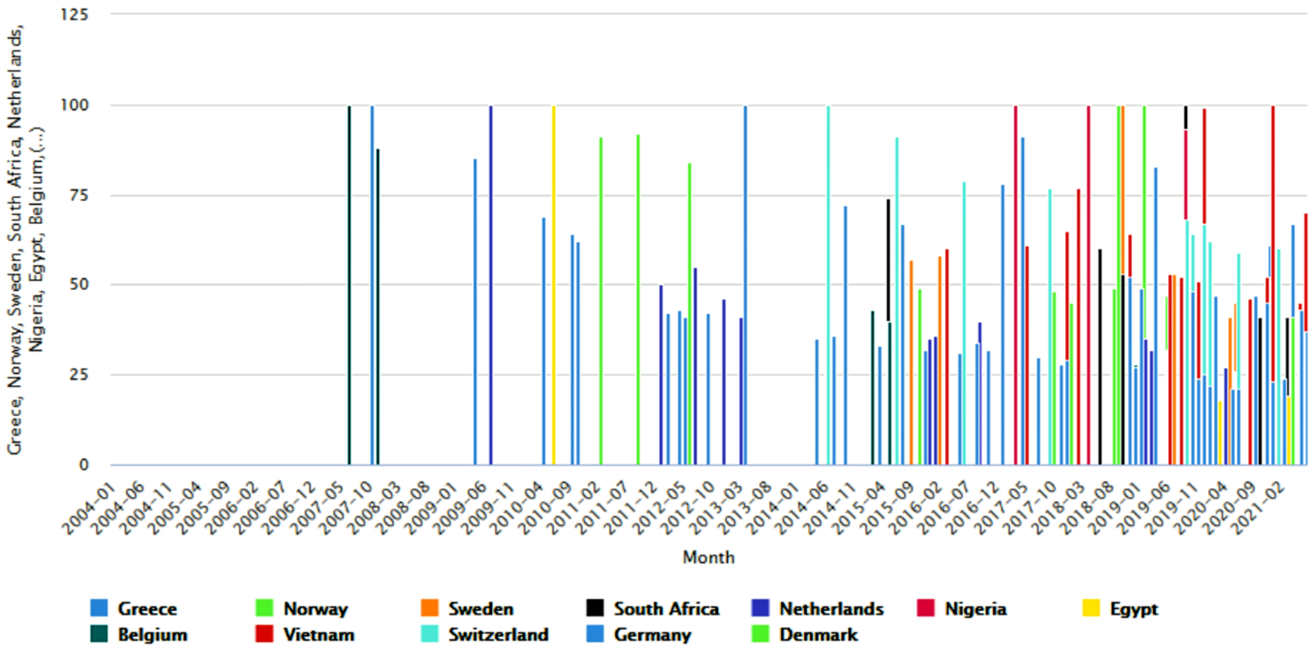

Figure 2. Data visualization that shows the varying patterns of interests related to fall detection from 2004–2021 for the countries—Greece, Norway, Sweden, South Africa, Netherlands, Nigeria, Egypt, Belgium, Vietnam, Switzerland, Germany, and Denmark.

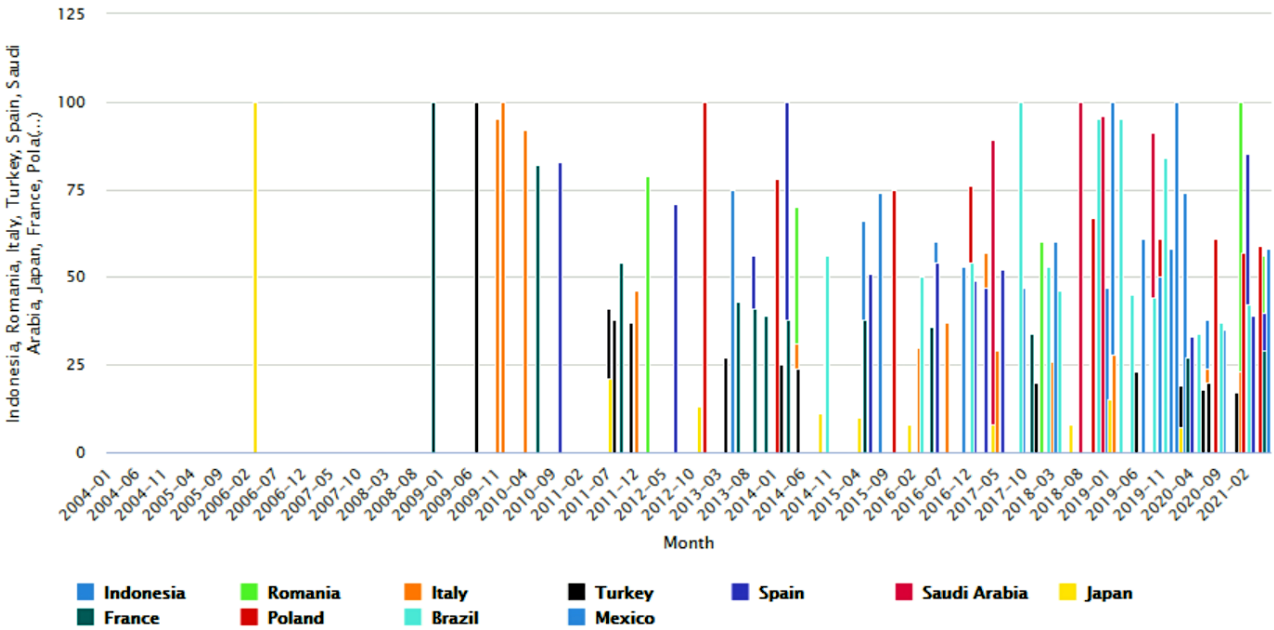

Figure 3. Data visualization that shows the varying patterns of interests related to fall detection from 2004–2021 for the countries—Indonesia, Romania, Italy, Turkey, Spain, Saudi Arabia, Japan, France, Poland, Brazil, and Mexico.

We performed this visualization using RapidMiner [82]. RapidMiner is a software application development tool that allows the development and implementation of various Big Data, Machine Learning, Pattern Recognition, Artificial Intelligence, and Information Retrieval-related algorithms. We used the educational version of RapidMiner Studio, with version number 9.9.000, on a Microsoft Windows 10 computer with an Intel® Core™ i7-7600U CPU @ 2.80 GHz, two core(s), and four logical processor(s), for this study.

3. Research Methods

This section presents the methodology that we followed for the development of this dataset. The study was performed in Google Trends [68] by analyzing the worldwide Google search data originating from different countries related to fall detection from 2004–2021. Figure 4 shows the Google Trends website and its user interface that allows studying and mining online search trends related to any topic, industry, individual, etc., in a given timeframe.

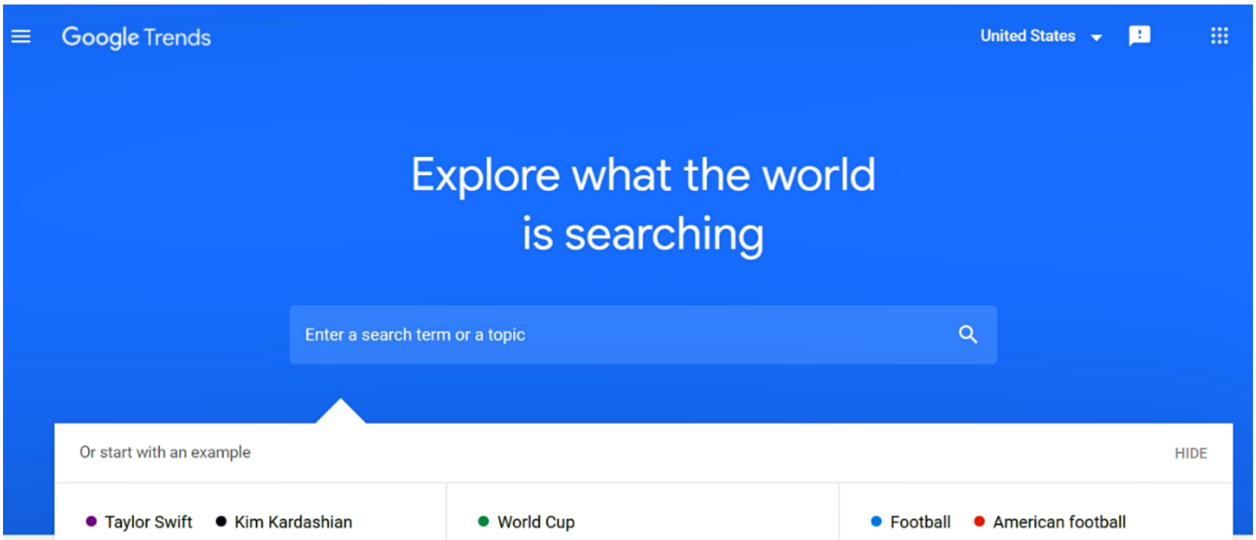

Figure 4. Screenshot from the Google Trends website that allows entering a search query to study the related search interests.

To conduct this study, we had to select the right set of keywords. Here, the right set of keywords would be those phrases or words that have been mostly used to refer to fall detection-related systems, technologies, applications, tools, and/or gadgets. Therefore, we surveyed a total of 59 works related to fall detection, out of which the first 30 works [13–42] have focused on presenting and discussing the needs and interests related to fall detection in different countries of the world and the remaining 29 works [83–111] are recent approaches which focused on various advancements in fall detection research. These recent approaches for fall detection have explored the intersections of multiple disciplines and may broadly be classified into three generations—Generation 1, Generation 2, and Generation 3, based on their functionalities, applicability, operational characteristics, performance, and user acceptance, as presented in the comprehensive review of fall detection-related works in [13].

The objective of performing this survey on 59 works related to fall detection was to develop a bag of words model [112] that would consist of the phrases and words that have been commonly used by the authors of these 59 works [13–42,83–111] to refer to the associated fall detection-related systems, technologies, applications, tools, and/or gadgets. The objective of this was to study these respective words and phrases to identify the right set of keywords for our Google Trends-based study by taking into consideration the frequency and relevance of these associated words and phrases. This bag of words model consisted of a total of 311 words represented in the form of 68 phrases that we manually extracted from these works [13–42,83–111]. This is represented in Table 3.

Table 3. The list of words and phrases that were used to develop the Bag of Words model from the 59-fall detection related works that were surveyed for this study.

Bag of Words	
fall detection system	falls among community-dwelling
Inclinometer Based Approach to Fall Detection	falls in elderly in Brazil
Fall Detection through Thermal Vision Sensing	fall-related injuries among older adults
activity classification and fall detection	falls among community-dwelling
Address-Event Fall Detector	fall prevention protocol
Algorithm for Elderly Fall Detection	Falls among community-dwelling
Posture Analysis in Fall Detection	Falls in older people
Fall Detection Using Principal Component Analysis	falling and risk factors of falling
Fall Detection Based on Body Part Tracking	Knowledge and perception of falls
Fall Detection with Wearable Cameras	Fall at home
Triaxial Accelerometers for Elderly Falling	epidemiology of fall
Smartphone-Based Data Mining for Fall Detection	fall injury
Falling Detection Using Multiple Doppler Sensors	fall-related hip fractures
vision-based approach for fall detection	fall risk scores
Wi-Fi-CSI-Based Fall Detection	Risk factors of falls
helmet design for drowsiness and fall detection	Fear of falling and cognitive impairment
Fall Detection using Human Skeleton Features	Falls and other geriatric syndromes
AAL fall detection system	Self-reported fall
Indoor Fall Detection in Videos	risk factors for falls
Smartwatch-Based IoT Fall Detection Application	Wearable sensors for reliable fall detection
multi-sensor patient fall detection system	accelerometry-based parameters for fall detection
Fall Detection Algorithm Based on Gradient Boosting	smartphone-based fall detection system
Fall Detection System using XGBoost	wearable system for pre-impact fall detection
Practical Fall Detection Algorithm	fall detection in a supportive home environment
Fall Detection System Using Smartphones	depth data for fall detection
fall detection in assisted living	pervasive fall detection system
elderly fall	tri-axial accelerometer fall detection algorithm
falls in older people	vision-based fall detection
falls among the elderly	microphone array system for automatic fall detection
health promotion program	camera-based fall detection system
falling and fracture in elderly people	Device-free fall detection
injury mortality in the elderly	Fall detection from human shape
fall risk assessment	viewpoint-independent statistical method for fall detection
Fall prevalence	wearable-sensor-based fall detection system

Thereafter, we used these phrases to generate a word cloud to determine those sets of keywords with the highest frequency and relevance for using the same in our study. A word cloud (also known as a tag cloud or wordle or weighted list in visual design) is a novelty visual representation of text data, typically used to depict keyword metadata (tags) on websites or to visualize free-form text. Tags are usually single words, and the importance of each tag is shown with a different font size or color [113]. This word cloud was generated by using monkeylearn [114] and is shown in Figure 5. Monkeylearn [114] was selected for the development of this word cloud because of its unique features as compared to other word cloud generators, which include—(1) artificial intelligence algorithms that can be directly run to help spot collocations, i.e., words that often go together; (2) features to automatically group similar words as per the concepts of stemming [112]; (3) editing of original text for removal of stop words [112] or other words that need to be eliminated from the word cloud; and (4) customization and analysis of the generated word cloud in terms of font, color, theme, and word quantity. In the process of generating this word cloud, we also performed tokenization [112] to calculate the frequency and relevance of each word and phrase that commonly occurred in this bag of words. This is shown in Table 4.

Table 4. The frequency and relevance of each word and phrase commonly occurred in the bag of words that was developed.

Word or Phrase	Frequency	Relevance
fall	61	0.427
detection	39	0.284
fall detection	38	0.379
fall detection system	9	0.995
detection system	9	0.19
based fall detection	5	0.569
fall detection algorithm	3	0.427
risk factors	3	0.284
community	3	0.142
vision	3	0.095
based approach	2	0.190
older people	2	0.190
events fall detector	1	0.142
based data mining	1	0.142
smartphone-based data	1	0.142
impact fall detection	1	0.142
indoor fall detection	1	0.142
reliable fall detection	1	0.142
fall risk assessment	1	0.142
fall detection application	1	0.142
body part tracking	1	0.142
practical fall detection	1	0.142
fall prevention protocol	1	0.142
related hip fracture	1	0.142
elderly fall detection	1	0.142
free fall detection	1	0.142
automatic fall detection	1	0.142
health promotion program	1	0.142
fall risk score	1	0.142
perception of fall	1	0.142
supportive home environment	1	0.142
independent statistical methods	1	0.142
factors of fall	1	0.142
microphone array system	1	0.142
epidemiology of fall	1	0.142
IoT fall detection	1	0.142
based iot fall	1	0.142
principal components analysis	1	0.142
multiple doppler sensor	1	0.142
helmet design	1	0.095
wearable system	1	0.095
activities classification	1	0.095
posture analysis	1	0.095
human skeleton	1	0.095
reported fall	1	0.095
fall prevalence	1	0.095
depth data	1	0.095
fall injury	1	0.095
injury mortality	1	0.095
wearable camera	1	0.095

Based on the data shown in Table 4, the word cloud was generated using monkeylearn [114], as shown in Figure 5. In Figure 5, the size of each word or phrase is directly proportional to its frequency. Or in other words, in Figure 5, a word or phrase that has a higher frequency is assigned a greater font size as compared to a word or phrase with a lower frequency. Different font colors were used to distinguish these words and phrases, and the font colors are not related to the frequency or the relevance of the associated words or phrases. Based on the findings from the word cloud presented in Figure 5 and Table 4, it can be observed that the phrases "fall", "detection", and "fall detection" have the highest frequency. Their respective frequencies being 61, 39, and 38. In terms of relevance, it can be observed that the phrase— "fall detection system" has the highest relevance of 0.995, and then the above-mentioned phrases "fall", "detection", and "fall detection" follow with their respective relevance values being 0.427, 0.284, and 0.379. Based on the same, it can be concluded that selecting the phrase "fall detection" would be the most appropriate and relevant for conducting our Google Trends-based study to gauge user interests based on web behavior data related to fall detection systems, technologies, applications, tools, and/or gadgets.

Figure 5. Word cloud generated using monkeylearn by using the bag of words model which we developed that consists of the words and phrases that researchers have used to refer to fall detection systems, technologies, applications, tools, and/or gadgets.

Thereafter, we entered these keywords on Google Trends to evaluate the associated user interests for each country from the above-mentioned list of 193 countries (Table 2) on a monthly basis from 2004–2021. Google Trends allows limiting the results related to user interests for a specific set of keywords to one geographic location. So, we used this feature and found out the user interests related to fall detection in each of these countries by selecting one country at a time. The total process involved 193 iterations where each iteration was different from the other in terms of the associated country whose interests in fall detection were being mined.

On the Google Trends website, we selected "all categories" to include all kinds of searches related to the keywords "fall detection", and finally, we narrowed down our search to "web search" to include only the results from google web search and exclude all search results related to google shopping and image searches. After that, we selected the time range as 2004 to Present. Upon entering these details, we were able to download the .csv file that represented the user interest data related to fall detection based on relevant web behavior for each month from 2004 to the Present for a specific country. We merged the data from all these 193 .csv files to form one .csv file where each column represented the search interest data from a different country. Figure 6 shows this study for one such iteration where the specific country whose user interests related to fall detection were being investigated was the United States.

We would like to mention a couple of considerations related to our dataset. First, we performed the data collection, analysis, and interpretation for the month of June 2021 on 21 June 2021, and indicated the search interest values that we observed for different countries as the search interest values for those countries for the month of June. However, based on the varying patterns of search interests both at a global and country-specific level for the remaining days in the month of June, it is possible that when this study is repeated at any point after the publication of this paper, the observed search interest values and associated trends might be different for the month of June 2021 and the months thereafter. Second, all the data from 2011 and thereafter in our dataset is as per improvement in the geographic assignment that Google Trends applied on 1 January 2011.

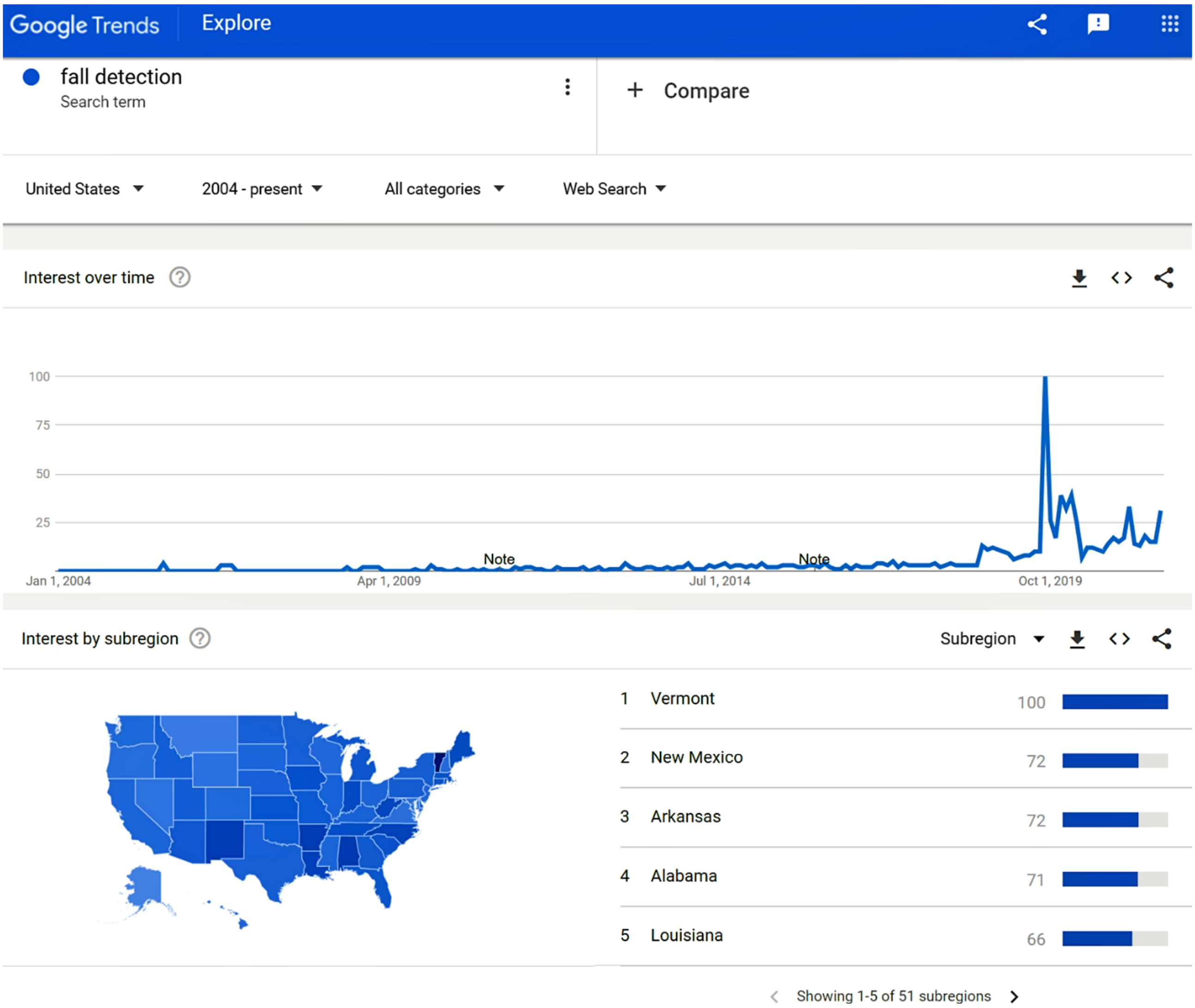

Figure 6. Screenshot from the Google Trends website where the user interest related to fall detection was studied from 2004–2021 based on the different criteria as outlined above, for the United States.

4. Potential Applications

This comprehensive open-access dataset that consists of fall detection-related interest data from 193 countries of the world for every month from 2004 to 2021, to present the overall interest and need related to fall detection at a country-specific level, is expected to have multiple applications and use cases to advance research and development related to fall detection both at a global level and at a country-specific level. To further support the same, we have presented 22 research questions (RQ) for investigation and evaluation by scientists and researchers working in this field using this dataset. These RQ's were developed based on studying and analyzing emerging and potential research directions in the interrelated fields of Big Data, Data Mining, Information Retrieval, Natural Language Processing, Data Science, and Pattern Recognition in the context of fall detection research. The RQ's are presented as follows:

RQ1. Is the rising interest in fall detection in any geographic region an indicator of the increase in falls in elderly people in that region?

RQ2. Does the increasing trend in fall detection in a country have a positive correlation with its healthcare-related and medical expenses (hospitalizations, emergency treatments, caregivers, etc.) due to elderly falls [115]?

RQ3. Is the interest in fall detection in a nation directly proportional to the fatalities related to falls in that nation?

RQ4. Does the increasing trend in fall detection from a country represent more advances in research and development related to fall detection in that country?

RQ5. Is the interest in fall detection directly proportional to the success or failure of fall detection-related awareness and prevention programs as well as initiatives by different geographic regions of the world?

RQ6. Does the increasing trend in fall detection in a country reflect an increase in sales of fall detection systems, applications, and gadgets manufactured in that country?

RQ7. Can the increase in interest related to fall detection be interpreted as an increase in the market potential of fall detection solutions both at a global and country-specific level?

RQ8. Do the varying trends related to fall detection in a geographic region have any positive or negative correlation with the user acceptance and trust of existing fall detection-related solutions available in that region?

RQ9. Is the increasing trend in fall detection from a specific geographic region an indicator of the increase in scientific and research inquiry and investigation (such as publications in the form of patents, papers, etc.) related to fall detection from that region?

RQ10. Can the patterns in the trends of user interests related to fall detection be used to train a machine learning model to forecast any short-term or long-term changes in these trends?

RQ11. Is there a correlation between the dynamic changes in trends in fall detection at a specific region and the social sentiment [116] related to fall detection technologies in that region?

RQ12. Does the increasing trend in fall detection in a region indicate an increase in the number of elderly affected by Alzheimer's and/or user interests towards Alzheimer's in that region, as falls may be an early indicator of Alzheimer's [117]?

RQ13. As falls are an early sign of Parkinson's disease [118], whether an increase in trends of falls in a region indicate an increase in Parkinson's disease in the elderly and/or user interests towards Parkinson's in that geographic region?

RQ14. Is there any association between the strict to moderate stay-at-home guidelines on account of COVID-19 [119] in a specific region with user interests related to fall detection originating from that region?

RQ15. Is there any positive correlation between the trends of falls in the elderly and loneliness in the elderly [120] at a specific time in a certain region, and can the study of one of these trends be helpful to predict the trends in the other?

RQ16. Studies have shown that falls have an association with high-risk medication use [121], chronic diseases [122], lower urinary tract symptoms [123], schizophrenia [124], depression [125], visual impairment [126], anxiety [127], sarcopenic obesity [128], and cardiovascular diseases [129] in the elderly. Can the trends and patterns in fall detection in a specific geographic region be studied to predict one or more of these issues or challenges faced by the elderly in the same region?

RQ17. Does the increasing or decreasing trend in interests related to fall detection relate to an increase or decrease in a specific sentiment (positive or negative) towards fall detection expressed in online communications, such as from social media?

RQ18. Does the increase in search interest (inferred by a higher search interest value) at a given point of time indicate an increase in online communications and exchange of information related to falls, for instance, an increase in the number of Tweets or Facebook posts related to fall detection at that time?

RQ19. What are the topics and online queries [130] on Google Trends that are related to fall detection, and is there any correlation in their trends with the trends of user interests associated with fall detection?

RQ20. Does any correlation exist between trends in fall detection and trends in robot-assisted living or ambient assisted living as per the methodology of studying and comparing relative search volumes of topics described in [131]?

RQ21. Do the trends in infodemic monikers, defined as a term, query, hashtag, or phrase that generates or feeds fake news, misinterpretations, or discriminatory phenomena [132], related to fall detection based on relevant google search data, help to determine the infodemic monikers related to fall detection on other online or social media platforms such as Twitter, Facebook, or Instagram?

RQ22. Can the characteristics of trends in fall detection, the related topics, and online queries [130] for a specific month in a specific geographic region be an indicator of trending topics [133] related to fall detection on social media platforms such as Twitter, Facebook, or Instagram, in that timeframe in the same geographic region?

5. Conclusions

The world is seeing an unprecedented increase in the elderly population and falls in the elderly are a serious concern. In the recent past, the rate of falls has drastically increased in certain countries of the world, specifically in the low- and middle-income nations. Falls in the elderly are associated with various forms of healthcare, medical, caregiver, and economic needs that vary from country to country. The ability of a country to support these diverse needs associated with elderly falls depends on the timely identification and evaluation of such needs as well as the interpretation of the underlining trends demonstrated by the data representing these needs. Timely anticipation and identification of such needs and the associated trends would allow such countries to address the same by using its existing resources, or by developing new policies and initiatives, or by seeking support from other countries or international organizations dedicated to global public health: for example, the World Health Organization and United Nations. To address these challenges, it is the need of the hour to conduct a study to identify, evaluate, and interpret these needs and the associated trends related to elderly falls arising from all the countries of the world. As the world is moving towards an Internet of Everything lifestyle, the global population is spending more time on the internet as well as communicating their needs and requirements via the same. Google Searches account for an overwhelming majority of online searches by individuals globally as well as in almost all geographic regions of the world. Researchers have investigated relevant web behavior data obtained from Google Searches in the form of user interests towards a specific technology, topic, or application to interpret the public health need, sales outlook, consumer acceptance, the use and applicability of the technology. Search interest data has also been investigated by healthcare researchers to interpret the needs associated with various disease outbreaks.

In view of this immense potential of Google Search data in today's Internet of Everything era to address the above-mentioned challenges, in this paper, we performed a comprehensive study using Google Trends where we used the latest advancements from several disciplines such as Big Data, Data Mining, Information Retrieval, Natural Language Processing, Data Science and Pattern Recognition. Our study makes two scientific contributions to this field. First, we have presented the findings of our study in the form of an open-access dataset available at https://dx.doi.org/10.21227/85jy-7m92. The dataset consists of user interests related to fall detection for every month for all the 193 countries of the world in a country-specific manner from 2004–2021. Second, by studying and analyzing emerging and potential research directions in different disciplines in the context of fall detection research, we present 22 research questions that researchers in this field can study, evaluate, and investigate based on the characteristic features of the data present in this dataset. As per the best knowledge of the authors, no similar work has been done so far. Future work would involve investigating these research questions and coming up with new ones to advance research and development in this field.

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