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SUSTAINABLE DEVELOPMENT IN MEDICAL APPLICATIONS USING NEURAL NETWORK ARCHITECTURE

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Abstract. The purpose of this research is to propose a methodology utilizing machine learning techniques to support medical organizations in effectively managing risks. Specifically, the study aims to connect social media data to identify and assess potential threats, ultimately enabling healthcare management to make informed decisions for their organizations and clients. The research employs machine learning algorithms to analyze user-generated content on social media platforms, generating comprehensive visual representations of various risk categories and their magnitudes. Additionally, the study utilizes data simplification techniques, including categorization, to streamline data processing and enhance overall efficiency. A computational framework is also developed, incorporating closed-form connections for threat assessment and evaluation. The study further empirically analyses the Consumer Value Stores (CVS) established for medical care in the United States. The findings reveal that prevalent threats within the lower quartile of client messages about CVS services include operational, financial, and technological risks. The severity of these risks is distributed among high risk (21.8%), moderate risk (78%), and minimal risk (0.2%). The research also presents several metrics to demonstrate the robustness of the proposed framework, confirming its effectiveness in effectively identifying and addressing potential threats. This research provides insights that can help healthcare management make informed decisions and foster a safer and more secure environment for their organizations and the people they serve.

Key words: Conversational Interpretation, Artificial Intelligence, Internet-based Information Mining, Medical Analytics, Risk Administration.

1. Introduction. Energy usage is experiencing a notable shift, moving away from traditional fossil fuel reliance and adopting alternative energy sources. Consequently, it becomes crucial to investigate the potential correlation between decreased electricity consumption and the enhancement of Green Total Factor Productivity (GTFP). This research explores various technical methodologies that can effectively merge the dynamic relationship between energy conservation and GTFP. The interplay of Artificial Intelligence (AI) and the natural resource market profoundly impacts GTFP in a bidirectional manner. Focusing on China as a case study and employing a pertinent mathematical model, the research delves into how AI fosters environmentally sustainable economic growth. AI's impact on carbon intensity varied significantly across various industries and developmental stages, underscoring notable strides in decreasing carbon intensity during the Eleventh Five-Year Plan compared to the previous period [1].

The sectors reliant on labour and technology are predicted to witness a more significant reduction in carbon intensity attributable to AI and the dynamics of the natural resources market, in contrast to enterprises heavily dependent on capital. Furthermore, this study anticipates that the nonlinear impact of machine learning and the environmental marketplace on the overall productivity of green factors will continue to follow a "U" shaped trajectory shortly. This research formulates a quadratic equation to characterize the intricate relationship between artificial intelligence and sustainable total factor production, drawing upon the latest advancements and research in AI [2].

The impact of artificial intelligence on the overall productivity of green industries exhibits a mixed character, encompassing both advantageous and adverse effects. Given the potential complexities associated with the productivity of various factors within green industries, this study examines AI's nonlinear influence on green total factor efficiency. To achieve this, the research employs a comprehensive approach, integrating a regressive dynamic panels regression model and a differential technique of moments alongside systems GMM, considering the inherent complexities of the system dynamics [3].

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The authors investigate the potential impact of artificial intelligence on carbon dioxide emissions within China's industrial sector, commencing from 2006 and extending through 2018. Remarkably, a discernible correlation is observed between the increased deployment of manufacturing robots and a corresponding reduction in carbon intensity. However, our findings suggest that artificial intelligence, on the whole, exerts a detrimental influence on China's greenhouse gas emissions, thereby emphasizing AI's multi-layered role in sustainable industrial practices [4].

The initial empirical evidence substantiates artificial intelligence's positive impact on carbon emissions. Notably, the findings underscore the variability of AI's influence on carbon intensity, contingent upon the specific developmental stage and industry. The efficiency of AI in limiting greenhouse gas emissions in China has exhibited marked improvement, coinciding with the nation's increased capacity for technological absorption and the production of a skilled robotic workforce. Furthermore, in contrast to enterprises heavily reliant on capital, sectors emphasizing labour and technological integration are composed to witness a more pronounced reduction in their environmental footprint, owing to the integration of AI. This underscores the differential impact of AI adoption across various industrial sectors, explaining the intricate relationship between technological advancements and environmental sustainability [5].

The paper indicates a significant influence of the six variables considered, delineating their crucial roles in the potential establishment of smart towns in Nigeria. Particularly, factors about the environment, technological advancements, societal dynamics, and legal frameworks are progressively gaining prominence, underscoring their critical contributions to developing and realizing smart town initiatives in the Nigerian context. Applying a comprehensive fuzzy synthesis approach offers a realistic perspective on the challenges that necessitate resolution before the aspiration of establishing smart cities in developing nations can be actualized. This lays a robust theoretical foundation for future research endeavours focused on implementing smart cities in developing countries, particularly Africa, where environmental and socioeconomic conditions resemble those observed in the Nigerian context. It notably establishes a firm conceptual framework for further exploration in this domain [6, 7].

The nation faces many pressing challenges that demand immediate attention before any meaningful strides can be made toward realizing the potential of urban regeneration. These challenges encompass elevated rates of development, growing populations, deficient foundational infrastructure, socioeconomic inequalities, inadequate legislative frameworks, financial instability, and governance deficiencies. Therefore, the insights collected from this research hold valuable implications for governmental authorities and other stakeholders responsible for urban development, emphasizing the critical issues that necessitate resolution [8].

Policymakers must prioritize addressing these fundamental challenges to foster societal equity and promote the advancement of the nation's population. While this research has limitations, it offers valuable insights into the complex challenges of developing smart towns. The employed methodology remains critical, suggesting that future studies could benefit from an integrated approach combining the Delphi methodology for validating issues identified in the primary literature, supplemented by other statistical assessment methods. Such an approach promises a more comprehensive understanding of the intricate obstacles to advancing intelligent urban centres [9].

The smart town concept represents a pragmatic response to the multi-layered challenges modelled by global industrialization. Across the globe, technological advancements, including the Internet, the Internet of Things (IoT), artificial intelligence (AI), and data analytics, are increasingly being harnessed in communities to enhance transportation, construction, healthcare, and social services. Cities are fostering digitization and entrepreneurial growth by deploying electronic infrastructure, fostering local economies and strengthening community well-being. However, the growing smart town industry is concurrently characterized by a propagation of fragmented smart city marketplaces and initiatives, engendering concerns surrounding governance, environmental coherence, and operational consistency [10].

In pursuing sustainable development, the enhancement of human health must be intricately woven into the fabric of societal and technological progress, along with environmental preservation. Achieving this necessitates the establishment of resilient frameworks and processes and meticulous risk management to mitigate potential threats. Administrative challenges, financial risks, and technology-related perils represent only a fraction of the myriad hazards medical organizations might face, particularly those operating within the digital era. Therefore, providing exceptional services for individuals and businesses necessitates the adoption of cutting-edge methodologies, such as machine learning, to effectively detect, assess, and address these challenges [11].

Machine learning and other AI-driven techniques are frequently utilized for textual analysis and semantic extraction. The Natural Language Processing (NLP) field emerged at the convergence of semantics and AI during the mid-20th century. Initially distinguished from Information Retrieval (IR), NLP effectively sorts and retrieves substantial text volumes through highly scalable statistical algorithms. Leveraging NLP for identifying medical conditions within digital medical records has proven instrumental in addressing multiple healthcare challenges, including monitoring diseases associated with medical care. For instance, inpatient admission rates for individuals with Chronic Obstructive Pulmonary Disease (COPD) serve as an indicator of a healthcare system's efficacy [12].

Social media's increasing influence and rapid expansion significantly impact the healthcare industry. The Internet has notably revolutionized patient interactions, providing a platform for discussing everything from support groups and the latest research to prescriptions and healthcare providers. Consequently, analyzing customer engagements on social media platforms enables medical organizations to gain comprehensive insights and improve their competitive edge. Furthermore, integrating advanced business data solutions supports optimizing risk management within healthcare facilities [13].

This research introduces an intelligent language processing framework that harnesses social media as a sophisticated data repository to enhance risk management practices within medical organizations. Moreover, the model incorporates categorization techniques and extensive data analysis methodologies to streamline data processing, facilitating more precise information handling. The study presents an algebraic overview of this framework and formulates risk analysis, identification, and assessment equations. A case study of the CVS Pharmacy Foundation in the United States is included, providing guidance on identifying and evaluating potential organizational threats. Finally, various performance indicators are scrutinized to validate the efficacy of the proposed framework [14].

2. Related Works. Transforming a city into a smart town is a complex and extensive undertaking, demanding the active engagement of multiple stakeholders and the ability to assess the potential of various novel computing technologies for enhancing a wide array of municipal operations. Consequently, the leadership and management of the smart city bear a significant responsibility. The study's proposed Smart City Conceptual Framework (SCCF) aims to assist municipalities in achieving this ambitious objective [15].

The Smart City Competency Model (SCCM) evaluates smart cities from administrative and technical perspectives. It equips participants with the tools to steer their cities toward a data-driven, technology-backed smart city transformation. In developing the SCCM, considerations are given to aspects encompassing strategy, internet integration, governance, and stakeholders. These core elements are supplemented by sub-components, collectively establishing robust connections and fostering a systematic approach to smart city planning, development, and implementation [16].

To more effectively manage the complex ecosystems associated with smart cities and the rapid evolution of digital technologies within urban landscapes, the study introduces and discusses the SCCM framework. This framework aims to address the resource constraints encountered by cities, which often lead to the failure of pilot smart city initiatives post-initial funding. The primary objectives of the SCCM involve facilitating the formulation of a long-term vision and plan for smart city practitioners, managing diverse interactions between stakeholders and digital infrastructures, and enabling the comprehensive assessment of associated risks and costs [17].

Central to the SCCM are the four key elements and their corresponding sub-components: strategy, technology, governance, and stakeholders. Together, the SCCM framework and its constituent components provide crucial linkages and a comprehensive approach to fostering the development of smart city initiatives and environments while removing barriers to establishing new enterprises and generating value within smart city ecosystems. Enhancing social responsibility depends upon integrating financial, social, and environmental perspectives. Within the context of smart city endeavours, a key objective frequently highlighted is enhancing residents' quality of life. Expanding the SCCM to encompass social and political dimensions makes developing environmentally sustainable and resilient smart cities attainable. Emphasizing the importance of indicators for monitoring and analyzing the multifaceted activities constituting a smart city project is crucial for ensuring its successful implementation and management [18].

In healthcare, the decision-making process is intricate, necessitating input from multiple stakeholders, and successful implementation relies on the assurance of long-term feasibility. The growing utilization of machine learning in healthcare has significantly improved medical and surgical decision-making by leveraging clinical data and statistics. However, the sustainable integration of AI-based decision systems in healthcare demands careful consideration of various factors. This study evaluates sixteen critical sustainability factors for integrating AI applications into medical decision-making, incorporating insights from 34 pertinent specialists in the Bangladeshi healthcare sector. The study ranks these factors based on expert opinions, highlighting areas of consensus and divergence [19].

The research applies data clustering techniques to categorize the variables into three distinct groups, each with essential implications for ensuring sustainability. The findings provide valuable insights for healthcare practitioners, aiding them in making informed decisions regarding integrating AI-based technologies in the healthcare sector of developing countries. The study acknowledges the potential bias introduced by respondents' subjective evaluations and employs various strategies to mitigate such bias. Future research efforts can benefit from a broader range of expert perspectives and additional metrics to ensure the investigation's objectivity [20].

In summary, this research underscores the current state of AI-driven applications in the medical sector, discussing their implications and challenges. It emphasizes the need for thoughtful approaches and strategic planning to fully connect the potential of AI, ensuring its effective integration in healthcare operations. The findings highlight the transformative impact of AI in the healthcare sector and advocate for continued exploration and implementation of AI-driven solutions to enhance overall healthcare outcomes and services.

3. III.Materials & Methods.

a) Mathematical Model This section will offer an algebraic elucidation of the proposed model, yielding several fundamental closed-form equations that can be employed for risk assessment, risk identification, and risk evaluation. The following segment will initially outline the fundamental notations in the "Abbreviation" section. Consider the postings made by individuals and others passionate about a particular medical institution as $Q_1, Q_2, Q_3, ..., Q_n$. The n, in this case, represents the total amount of threads analyzed. The group encourages its patients to share their feedback on the quality of care they have received on the Internet, where it may be added to the growing body of information on a scale between L_1 to L_n. We presume that every individual writes just one share, which may consist of many phrases.

$$Q = [Q_i]^T \tag{3.1}$$

The individual in need i for whom $1 \leqslant i \leqslant n$ and $1 \leqslant j \leqslant m$ exists has an expression value j, denoted by w_j, and $P_i = [w_j].Q_i = [w_j]$, where w_j is the individual i^{th} expression value.

$Q_i = [w_j]$ might store a considerable quantity of information structured in multiple manners, including nouns, verbs, and prepositions. To deal with the high complexity of the data supplied in Equation 3.1, we shall cluster the variables into distinct yet connected categories. The following equation may be used to find S:

$$S = max[Ky] \tag{3.2}$$

where y is the dataset's phrase y and Ky is a subject integer.

As a result, Equation 3.1 may be decomposed into more manageable chunks is given by:

$$Q = [Q_u]^T \tag{3.3}$$

where $u < i$.

The information exists in various representations, including words, predicates, terms, modifiers, etc. To reduce the amount of information, we must consider the most basic phrases: verbs, adjectives, nouns, and adverbs. Therefore, in Equation 3.1, the vector of words connected with the understanding vector has the form:

$$Q_i = [w_d], \text{where d¡j.} \tag{3.4}$$

A criterion that weights the basic terms based on three instances, like in the sections that follow, to analyze

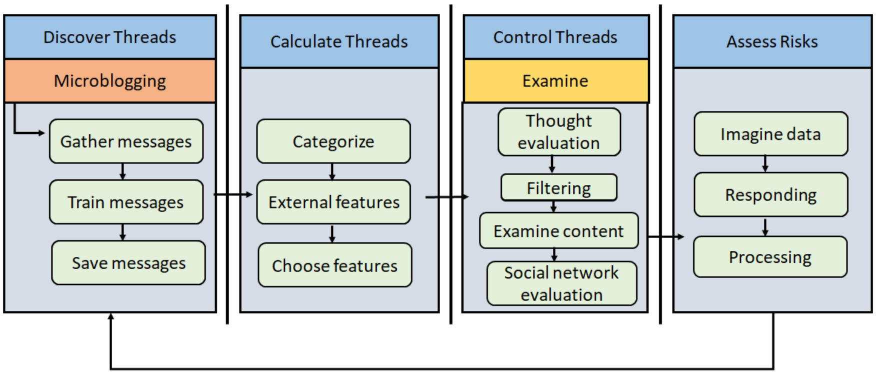

Fig. 3.1: Model of computerized risk handling in medical services

every individual's understanding:

$$Weight = \begin{cases} 0; \text{ no risk} \\ 0.5; \text{ potential risk} \\ 1; \text{ risk} \end{cases} \tag{3.5}$$

Using the conditions presented in Equation 3.5, we get an additional closed-form expression for measuring expertise:

$$L_v = \beta(\frac{Verb + Adverb + Noun + Adjective}{4}) \tag{3.6}$$

As a result, the value of Q_i in Equation 4.4 gives rise to an additional vector whose numbers are expressed in Equation 4.6. The shape of this vector is expressed as:

$$S_r = [L_u]^T \tag{3.7}$$

The risk assessment $Risk_{est}$ is specified as:

$$Risk_est = (R_1^2 + R_1^2 \sum_1^2 C_k - R_1 Pr - R_1 Pr \sum_1^2 C_k) \tag{3.8}$$

where $Pr \leqslant R_1$, C_k=level of risk.

b) Proposed Methodology The following section introduces a distinctive strategy integrating the Internet, comprehensive data analysis, risk management, and healthcare. Within this framework, risks are identified, assessed, controlled, and subsequently monitored. Figure 3.1 illustrates the classification of these stages into their respective categories. Medical institutions can effectively identify potential risks by utilizing social networking platforms throughout the various phases of the risk identification process. This can be achieved by monitoring and analyzing the online discourse on platforms such as Twitter, Instagram, Facebook, and YouTube.

Engaging in online dialogues concerning disseminating specific epidemics and other health concerns is essential for promoting awareness and conducting risk evaluations. This stage encompasses three separate procedures: information gathering (utilizing APIs, crawlers, and surveys), data scrubbing (eliminating erroneous data, including misleading information, incomplete details, and conflicting data), and data retention (utilizing databases constructed with NoSQL and Apache Hive, among other extensive storage facilities). The initial step in this stage involves data collection through APIs. Subsequently, the data cleansing process follows, and finally, data storage is executed.

During the risk assessment phase, examining online user behaviours can offer insights into potential hazards for medical enterprises. The primary objective is data collection. Aside from the number of hashtags, this type of engagement can be observed through the number of shares, likes, and comments generated for specific posts. Therefore, analyzing users' mindsets and anticipating the likelihood of adverse outcomes is imperative while capturing behavioural patterns from the amassed data. This delineates how, where, to what extent, and for how long hospital patients are frequently exposed to potential risks. Data classification, feature extraction, and feature selection constitute the three sub-steps within this segment.

A wealth of audiovisual content on social media platforms, including text, images, videos, and audio files, can be abundant. These records might be organized, partially structured, or unstructured. The classification process leverages various techniques, including Quantum Support Vector Machines, a MapReduce-based k-Nearest Neighbors approach, and Composite Artificial Neural Networks to manage big data's significant scale and diversity. This involves organizing the data into relevant subsets. Progressing to the subsequent stages necessitates the initial determination of categories from the preceding step, entailing the identification of multiple attributes and aggregating the features within each category.

Feature extraction transforms input data, including words and images, into attribute-value pairs. This enhances the compatibility of features for utilization in computational learning techniques. Leveraging a set of ordered data, the N-Gram, Lexicon-based attributes, Bag-of-Words approach, and Principal Component Analysis (PCA) are employed to generate the resulting metrics, thereby reducing the overall number of variables present in the initial dataset. The objective of attribute selection is to streamline data complexity and dimensionality by reducing the number of features within the set of extracted attributes, achieved through various methods such as Chi-Square (CHI) or Information Gain (IG).

The monitoring phase incorporates various analyses, including qualitative, diagnostic, predictive, and prescriptive, enhancing decision-making capabilities by fostering a deeper understanding of pertinent factors. Descriptive analysis is the initial step in data processing, encompassing the collection of essential archival data necessary for generating actionable insights.

The segment dedicated to the results of the experiments can also facilitate the computation of the proportion of specific findings relative to the entirety. Many techniques, including data mining, association, and exploration, can be harnessed to elucidate the diagnostic analysis process, rendering it more intricate research. Through statistical analysis, data can be transformed into valuable and actionable insights. Predictive analysis is ideally conducted in stages, with pivotal components encompassing transactional targeting, decision evaluation, and predictive forecasting. By scouring the landscape for actionable insights, predictive analytics illuminates new opportunities and helps mitigate potential threats.

Stakeholders and investors associated with medical enterprises now receive valuable guidance on current risks and mitigation strategies, thanks to the illustration of insights gleaned from the preceding phase. The anticipation is that appropriate measures will be taken once feedback is received. The effectiveness of these actions will hinge on how they are executed, thus underscoring the iterative and closed-loop nature of risk management in identifying and controlling risks.

4. Experimentation & Results. A prominent healthcare organization for CVS, headquartered in the United States, has established itself as a global leader in the medical industry. This fact led us to determine it as an ideal candidate for a comprehensive case study. In the middle of 2022, we employed the Twint tool to extract over 28,000 retweets, focusing on the geographical distribution of individuals.

a) Outcomes and Effectiveness Evaluations While scrutinizing the information pool for potential threats, we conducted an initial threat assessment. Each tweet's potential threat was evaluated using a threat assessment approach. The analysis revealed that the three most frequently mentioned locations were pharmacies, healthcare facilities, and stores, prompting us to concentrate on identifying the risks associated with these areas. A comprehensive lexicon was compiled, comprising over 8000 risk-related words and phrases, such as "hacking," "malpractice," and "dangerous."

Within this lexicon, the pharmaceutical category encompassed more than 6,000 messages, the healthcare category contained over 4,300 messages, and the retail category accounted for more than 2,500 tweets for risk evaluation purposes. The findings indicated that approximately 75% of the samples exhibited no concerns, while 25% or more of the specimens indicated the presence of potential hazards. Figure 4.1 presents the monthly

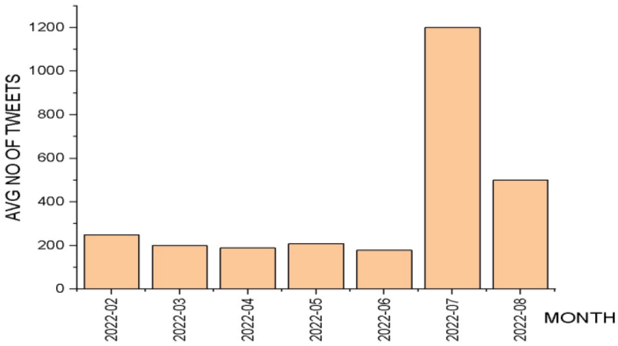

Fig. 4.1: The breakdown of tweets during six months

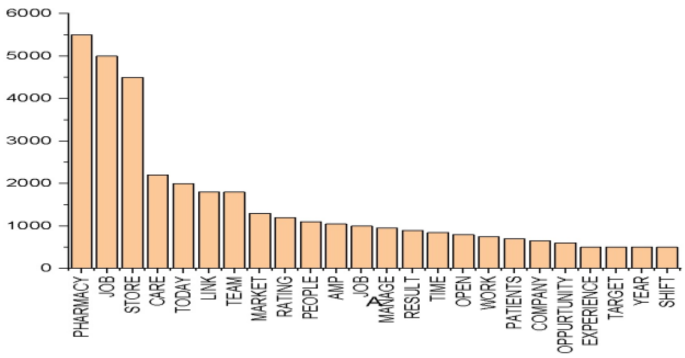

Fig. 4.2: Top-Frequency Keywords in the Information Dispersion

distribution of tweeted messages, while Table 4.2 provides several examples of comments indicating the absence of threats, the presence of potential risks, or identified risks.

The outcomes of employing Equation 3.2 to identify the most commonly occurring terms in the analyzed data are depicted in Figure 4.2. A range of performance metrics were employed to authenticate the results, including accuracy, precision, recall, and the F1 score. Given the challenges associated with annotating 28,000 tweets, we resorted to the principles of sampling statistics for assistance. To ascertain the required sample size, we applied the following formula:

$$t = (\frac{RT}{R-1+T}) \tag{4.1}$$

In this Equation, "T" stands for the sample proportion, and "R" stands for the error ratio. Because we have decided that the degree of conviction should be 96%, the Z-score will be the same as 1.95. In addition, the median divergence, equal to 50%, and the degree of erroneousness, equal to 5.5%, are identical. Consequently, the number of messages in the collection equals 378 when the initial values are substituted into Equation 2.9. The breakdown of the sample sizes into their respective categories is shown in Table 4.1, which can be seen below, and Figure 4.3 defines the distribution of risk categories for pharmacy as per model performance.

Now that the number of participants has been determined, we can annotate it and calculate the outcome metrics in Table 4.2. Figure 4.4 shows the model performance in risk category Vs storage.

b) The Complicated Nature of the Suggested Approaches

We zeroed down on the most important processes to determine the time commitment required by each suggested algorithm. The cost of the first method, which can be found in method 1, has a continuous loop. A second loop is included within this loop, and it is the one that moves across the rows of the matrix Qi. The

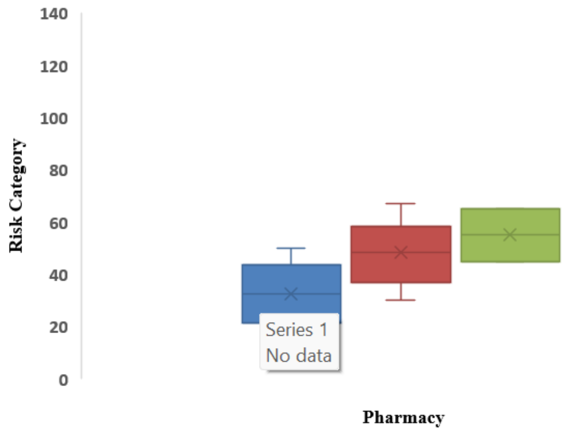

Fig. 4.3: Risk category vs. Pharmacy dataset

Table 4.1: Sample size dispersion by responsive

Data set size	Storage	Care	Pharmacy	Risk category
296	82	94	120	Zero Risk
11	3	4	4	Prospective Risk
119	22	54	43	Risk
426	107	152	147	Total

Table 4.2: Risk assessment metrics for success

S=426	Accuracy(%)	Recall(%)	F1 Score(%)	Precision(%)
Zero Risk	113	96	90	84
Prospective Risk	35	74	43	84
Risk	78	91	82	84

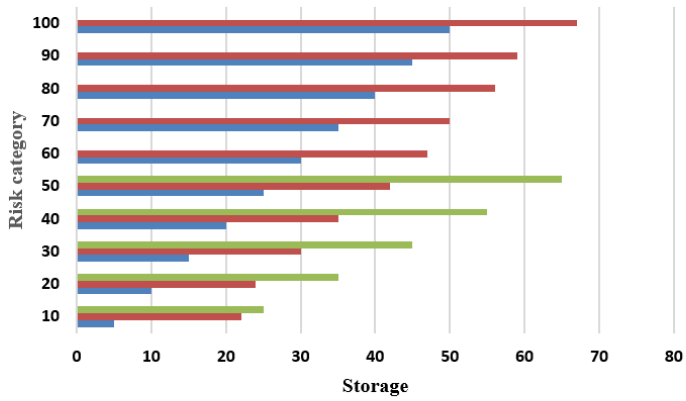

Fig. 4.4: Risk Category Vs Storage

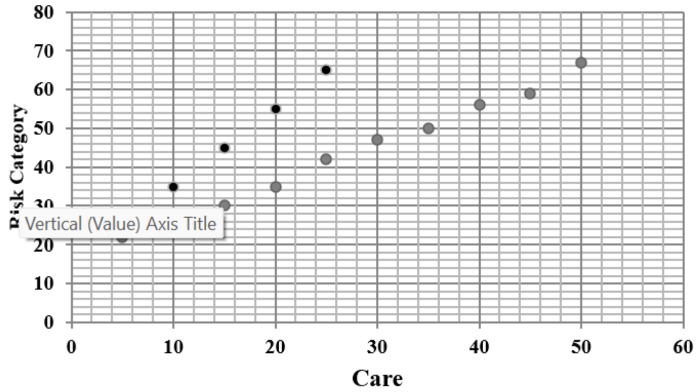

Fig. 4.5: Risk category Vs care

resulting matrix has a fixed number of rows, denoted by u, and columns, denoted by c, with the property that u ¿ i ¿ j (refer to Equation 3.2 and Equation 3.3). Therefore, the expenditure of this matrix is denoted by the notation O(V_c).

This approach involves looking for a word using two lexicons, one for risk keywords and another for potential phrases, where the expenditures are $O(n^2)$, and some essential if circumstances, where their costs are O(1). The first vocabulary is for risk phrases, while the second is for potential keywords. As a result, the total cost of the first method is denoted by the notation $O(n^2)$. Similarly, we utilized two vocabularies for each mechanism. Figure 6 defines the risk category Vs care. In this method, we used one vocabulary for risk terms and another for risk categories, one for risk words and the other for risk evaluations. Therefore, the time required for each of them to complete is $O(n^2)$.

5. Conclusion. The fundamental aim of this study is to employ an automatic language translation approach to detect and evaluate potential risks prevalent within medical facilities. In pursuit of this goal, the research capitalized on using social media as a contemporary and rich data source. The categorization techniques are strategically applied to streamline and manage the complexity inherent in the collected data, ensuring a more efficient and insightful analysis process. A significant outcome of the study is the derivation of a series of closed-form algebraic equations instrumental in enabling a comprehensive evaluation of the identified risks, facilitating their accurate assessment and subsequent management. A meticulous and detailed research is conducted focusing on the operations of the CVS institution, a prominent player in the American healthcare sector. This research provided a rich and informative exploration, analysis, and evaluation of the possible threats that could impact the institution's functioning and the well-being of its stakeholders. Also, calculating various essential metrics offers valuable insights into the proposed model's predictive performance. The research envisions incorporating additional methodologies. It further studies the precision and depth of the obtained findings, aiming to enhance the overall effectiveness and applicability of the proposed risk assessment model in healthcare management.

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