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RESEARCH ARTICLE

Real-Time HealthCare Recommendation System for Social Media Platforms

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ABSTRACT Biomedical services play a vital role in calibration and validation of services with the influence of social media platform and big-data processing toolkits such as ''Spark'', the processing and recommendation system can achieve a higher order of reliability and validation. In this research article, a novel framework is proposed to provide a recommendation of biomedical services from various social media platforms datasets. The framework is supported by a distributed processing technique under spark framework principle to segregate and process datasets based on SQL injection queries. The proposed technique's distributed datasets are trained and validated under a distributed storage. The Spark-bits are processed with a recommendation system for healthcare services. The technique deploys a fuzzy neural principle in cross-reference identification of recommended framework with supportive decision making. The categorization and adapting distributed programming and storage using Spark extracts relevance in recommended properties. These qualities support decision-making using Controlled Learning based Neural Networking model (CLNN). The proposed technique has provided a higher value of reliability in a real-time recommendation environment.

INDEX TERMS Healthcare recommendation, machine learning techniques, social media recommendation.

I. INTRODUCTION

Social media is the connected and self-space of this century. Millennials prefer to be self-present and attached to the social media platforms and tend to provide detailed activities and events via these platforms. Typically, social media is termed as ''New generations comfort space'', under social media various operations and activities are performed such as sharing emotions, daily activities, and events. With advancement of technology, the agenda of social media platforms have been enhanced with additional features and applications such as GPS tracking, location recommendation, sharing moments and much more. These features and applications have proposed major developments and wide verity of futuristic support in improving the life and standard of the community. In today's World an estimate of 5 billion users are actively participating in social media with day to day life event sharing. The contrast of subjects shared in the social media platforms have been inclusive of politics, health, current affairs and much more.

The scope of this article is to customize the recommendation system for the social media-based user querying. The recommendation system is inclusive of having an higher reliable assistance to provide systematic decision support for the requested information. With the help of these recommendations, an appreciated decision making and categorizing of various subjects is achieved. For instance, consider the example of handling Global pandemic, the role of social media in encountering the unprecedented situation is an exception. The platforms were used to track users in terms of the location, health, depression, interaction, primary contacts and much more. This internally, was achievable due to the recommendation algorithms incorporated with the platform. The agenda of this article is thus, to provide a user reliable recommendation on medical or healthcare services using the social media platform.

The proposed technique is developed using a distributed ecosystem of Spark toolkit. The spark-based user identification and attribute resolution is used to customize and

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process the interim bits of data on lager API's. These API's provide a reliable source for data collection for processing. The proposed technique thus provides a reliable context for recommendation and decision support of various healthcare services. This article is customized with an introduction followed by Literature reviews, in Section III and IV, the methodology of proposed technique and mathematical proof is discussed and validated. The results and discussions on outcome are briefed in Section V, followed by conclusion on the article with closing remarks for future enhancement.

II. LITERATURE REVIEW

The purpose of social media creation was to provide a reliable source for inter-networking and communicating with trusted users and peers. This provided a very basic utilization and customization channel with limited services. A detailed review and history of connectivity is discussed and reported by [1] under the book. The author has briefed the various critical aspects of social media evolution. This has incorporated various add-on functionalities and applications for enhancive utilization of connected networks. Since these networks are connected and have access to the channel, the security and authentication is a major challenge as discussed by [2] and [3]. These challenges are critical and have higher grounds of information corruption and conjunction. The future of these connections has created a recommendation framework [4] as a main frame entity for connecting multiple users. The recommendation systems were further enhanced by multimedia [5] datasets, this includes a random approach for optimizing and building a ecosystem for realize decision support.

The internal recommendations are discussed and categorized based on the subject and keywords. The medical paradigm for recommendation is based on attributes and user suggestions for improving the quality of decision. The [6] has discussed a reliable solution for medical data transfer and detection within a third-party channel. The MooM datasets are categorized into multiple segments based on type of dataset. This system is an inclusive approach for categorizing the recommendation or classifier for medical / healthcare systems. Thus, to encounter a challenge as discussed in [7] a typical approach of enhancive solutions are required using minimal infrastructural changes.

The benefits and limitations of social media and healthcare [8] is a major challenge for rectifying a self-learning approach of decision making. The reliability of system specific recommendation is important as the medical data is sensitive and has a higher order of dependency with attributes and parameters [9]. The scope and utilization of information and its behaviors in fundamental and scope of evaluation requires a sustainable solution with respect to modelling and attribute correction. The evaluation of remote recommendation of healthcare is proposed under an ICT norm [10] for optimizing and enhancing the pattern of evaluation. This article provides challenges and technological lags for enhancing the user experience while using remote healthcare services under telemedicine. Typically, the numerical patterns and evaluation is customized and progressed in [11] with numerical clustering of datasets for distributed computing under Controlled Learning based Neural Networking model based on mental health corrections and computation using speech signals.

The recommendation system also needs an understanding with a purpose of socializing healthcare recommendations [12]. With a structural approach of managing the information with respect to behavior model of datasets. This processing has improvised in [13] for current Global pandemic situation for customizing the healthcare recommendations. These approaches have developed a sustainable solution in decision making and supporting. The privacy and policy for improving the social media platform recommendations is discussed in [14] and, [15] to support the ethical and professional liabilities for commercialization the technological enhancements. The process of aligning recommendation of priority in treatment is another major challenge and motivation for this research [16]. The scope of recommendation is based on the scenario of IoT device token allocation and scheduling.

From Table-1 the literature summarizes major studies in this sector, emphasizing the need to fill research gaps to improve social media-based healthcare suggestions. These studies address security, privacy, ethics, and the necessity for personalized recommendation algorithms. User engagement metrics, cross-platform recommendation systems, and real-time recommendation algorithms are still poorly understood despite progress. Furthermore, there is a need for scalable and personalized recommendation systems to handle diverse healthcare needs effectively which are discussed in the upcoming sections.

III. METHODOLOGY

The process of recommendation and evaluation of services based on user search and demand is discussed in this article. The global user data via social media platform is collected and coordinated using a social media backend platform. The datasets are processed using dedicated API and exit sockets. These sockets provide a centric dataset to processes and evaluated overall data from the server. These datasets are raw and has larger spectrum of data and noise. Hence a scripted processing of focused attributes extraction is appended. The attributes are generally resolved using an independent dependencies parameter. At this phase, the datasets are centric and have attributes with higher order of dimensions.

The processing phase is further included with a recommendation processing unit and decision support for healthcare recommendation using user input via a keywords-based SQL injection query. The keywords (query) must be processed under a distributed processing unit, programmed and monitored under spark platform. These consist of a SPARL MLIB for a dedicated library management of queries and SPARK BITS to align the incoming queries into a structural processed instruction. The resultant values are then stored with

TABLE 1. Overview of studies on social media-based healthcare recommendation systems.

Sl. No.	Study	Performance Metrics	Research Gaps
1	Van Dijck (2013)	Evolution of social media connectivity	Lack of standardized performance metrics for comparing recommendation system effectiveness
2	Gritzalis et al. (2014); Kaplan and Haenlein (2010)	Security and authentication challenges	Need for comprehensive user engagement and satisfaction metrics
3	Sperlì et al. (2018); Amato et al. (2019)	Multimedia recommender systems	Privacy and security concerns persist despite advancements in recommendation algorithms
4	Ahmed et al. (2019); Grobler and Dhai (2016)	Ethical challenges in social media healthcare	Lack of research on cross-platform recommendation systems
5	Moorhead et al. (2013); Zhou et al. (2019)	Social media uses in health communication	Limited research on real-time recommendation algorithms
6	Yuan et al. (2018); Petrovski et al. (2020)	Socialized healthcare service recommendation	Need for real-world validation of recommendation systems
7	Zaman and Li (2014); Yu et al. (2021)	Semantics-enhanced recommendation systems	Incorporating user feedback and preferences in recommendation algorithms
8	Ahmed et al. (2021)	Neural Network Based Mental Depression Identification	Limited exploration of neural network-based recommendation systems for mental health diagnostics

a dedicated distributed server connected to build training datasets. These datasets are treated as the primary and aligned datasets for processing the recommendation of healthcare services. Parallel to the processing, the recommendation of healthcare services is initialized via distributed processing unit. A dedicated controlled learning neural networking model is processed and developed to handle parallel queries of various instructions via social media recommendations as shown in Fig. 1.

The datasets are further processed and provided with decision support using a trivial SVM based approach. The inter-junction of information is aligned and computed with a parallel processing and recommendation look-up approach over a trained dataset. These recommendations are updated, and decision support is provided. Further, the evaluation is discussed via a dedicated inter-dependent recommendation model in section IV.

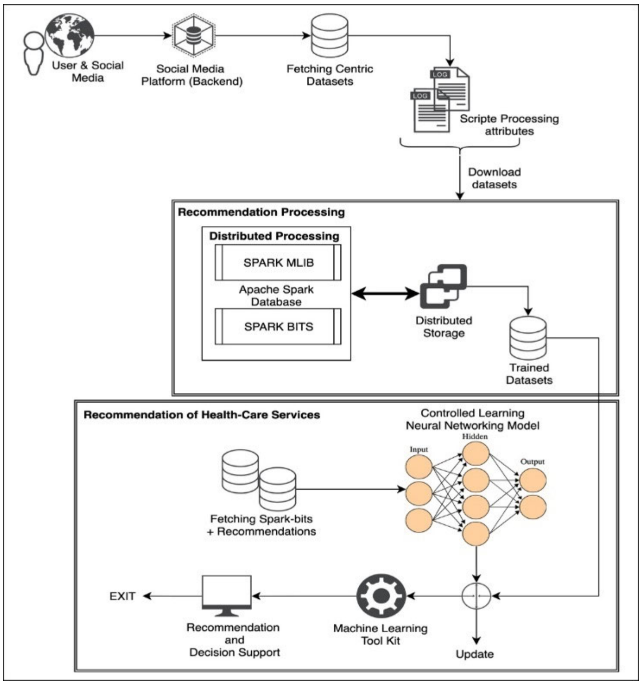

FIGURE 1. Proposed system architecture diagram.

IV. SPARK RECOMMENDATION SYSTEM

The proposed technique is designed and validated with reference to a recommendation system of queries based on spark platform. The approach is validated in the following modules.

1. User grouping and coordinates linkage
2. Recommendation processing
3. Distributed attributes co-relation extraction& mapping
4. Healthcare service recommendation technique
5. Decision support and Mapping

A. USER GROUPING AND COORDINATES LINKAGE

The proposed system architecture is dependent on social media validation for streamlining the data collection and fragmentation. The input stream of data bits are taken from tweeter API for coordination and amplification. The process of tweet and social media post is represented as $S = \{S\_1, S\_2, \cdots, S\_n\}$. Such that $\forall \delta a \in S$. Such that each correlated values are composed and fragmented as shown in Fig.2. The Fragment of each segment S_a is a bi-product of multiple social coordinates with relevance to social inter-connection as $\{S\_i\ \varepsilon\ S\_(n\text{-}1)\ |n\varepsilon\theta\}$. Where n is the number of datasets from social networks and θ is the variation constant of collecting maximum instances of given media recommendations. The

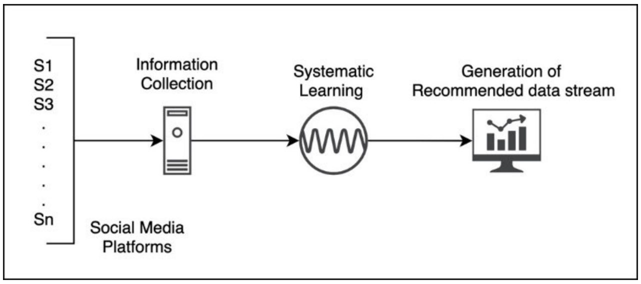

FIGURE 2. Recommendation phase.

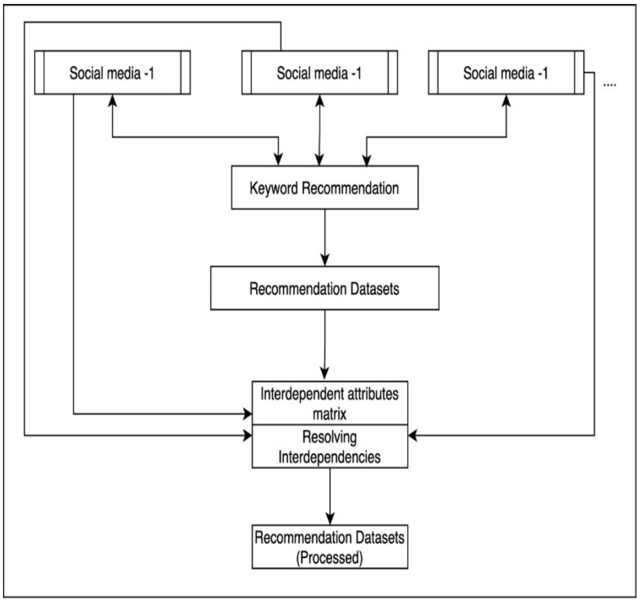

FIGURE 3. Representation of data dependency and multi-media inter-connectivity evaluation.

auxiliary of filter is altered with reference to Eq.1

$$T_\theta = \frac{\pi r^2 \theta \log_2 \left(\pi^2\right)}{P_i} . \lim_{n\to\infty} \frac{\delta\left(S_i\right)}{\delta t} . \Delta T \tag{1}$$

Thus, the coordination of each signal data (S_i) is collected under multi-indexing matrix as reference matrix for multiple media platform co-variables interconnection as shown in Eq.2, as shown at the bottom of the next page.

The correlation matrix of interconnected variables (i.e,) $\left(S_\theta, S_\beta, S_\alpha\right)$ are internally represented as $S_i \in \left(S_\theta, S_\beta, S_\alpha\right)$ and $S_i \in S$ with all internal parameters of evaluation. The each tweet or media post values of given keyword (K) is directly dependent and related with nearby values. These values and instances are further expanded in Eq.3, as shown at the bottom of the next page. The matrix evaluation is shown in Fig. 3. The given dataset (D_s) is further expanded and inherited with co-related matrix functions in each dimension of keyword reference as $k = (k_1, k_2, k_3, \ldots k_n)$ where $(\forall k_n \in k_i | i = 1, 2, \ldots n)$. The existence of each parameter (p_i) in (k_i) is shown in Eq.4 of inter-depended.

$$F = \lim_{n\to\infty} \left(\sum_{i=0}^{n} \frac{\delta\left(p_i\right)}{\delta t} - \frac{\delta\left(k_i\right)}{\delta t} \right) \tag{4}$$

$$\forall F = \lim_{n\to\infty} \left(\sum_{i=0}^{n} \frac{\delta\left(p_i\right)}{\delta t} \cap \frac{\delta\left(p_i+1\right) - \delta\left(k\right)}{\delta t} \right) \tag{5}$$

The occurrences of each functional value (F) is the resultant of systematic combination of parameters dependent in keywords (k). Hence, the relative matrix of multi-platform of social media i.e, $\left(S_\theta, S_\beta, S_\alpha\right)$ are relatively higher and mapped into the existence of F as each of $F_i \rightarrow \forall S_i | S_i \in S_\theta$ or $S_i \in S_\beta$ or $S_i \in S_\alpha$. These functional parameters are further expanded and retrieved from the dependency matrix as shown in Eq. 6.

With each independent platform value (F), the dependency matrix (θ, β, α) are resolved and refunctioned as shown in Eq. 7 and Eq. 8. The process is further expanded into the phase of recommendation.

B. RECOMMENDATION PROCESSING AND ATTRIBUTE MAPPING

The Recommendation system is decoupled as the process of developing an inter-dependent format of datasets collected via multiple social media platforms. The process of recommendation is supported by providing a relative weight and supports in the attributes and keyword dependent datasets. The weights are factor values representations of each independent recommendation in raw datasets as (w) with association to (S_i) as $(w \in S_i)$ under no-direct correlation. The fundamental paradigms of this recommendations is based on maximum threshold value (T_θ) and minimum threshold value (θ_0) as each weight is generalized as Eq.9.

$$F = \int_0^\infty \frac{\delta\left(T_\theta\right)}{\delta t} \cup \left(\sum_{i=0}^{n} \left(\frac{\delta\left(S_\theta\right) - \delta\left(S_\beta\right) . \delta\left(S_\alpha\right)}{\delta t} \right) \right) \tag{6}$$

$$\forall F = \int_0^\infty \frac{\pi^2 r . T_\theta}{\delta t} \cup \left(\sum_{i=0}^{n} \frac{\delta\left(S_\theta \cap S_\beta \cap S_\alpha\right)_i}{\delta t} \right) \tag{7}$$

$$\forall F = \int_0^\infty \frac{\pi^2 r . T_\theta}{\delta t} \cup \left(\sum_{i=0}^{n} \frac{\delta\left(S_\theta\right)_i}{\delta t} \cap \frac{\delta\left(S_\beta\right)_i}{\delta t} \cap \frac{\delta\left(S_\alpha\right)_i}{\delta t} \right) \tag{8}$$

The weight matrix (w) is relatively improved and optimized under multi-relative inferences of two peak threshold values (e_{max}, e_{min}) processed with reference to $(w)_n$ is relatively improved as value of (θ, β, α) is designed on dependability.

$$w = \lim_{n\to\infty} \left(\frac{\delta\left(w_{e_{max}} - w_{e_{min}}\right)}{\delta t} \right) .^{\Delta F} \tag{9}$$

The interactive approach of weight (w) are thus taken in constructive order of correlation as shown in Eq.10 and threshold (θT) is computed with a fragmented validation of informative weight (w) as shown in Eq. 11.

$$w = \lim_{n\to\infty} \left(\frac{\delta\left(w_{e_{max}}\right)}{\delta s} \cap \frac{\delta\left(w_{e_{min}}\right)}{\delta s} \right) \tag{10}$$

The interactive approach of weight (w) are thus taken in constructive order of correlation as shown in Eq.10 and threshold

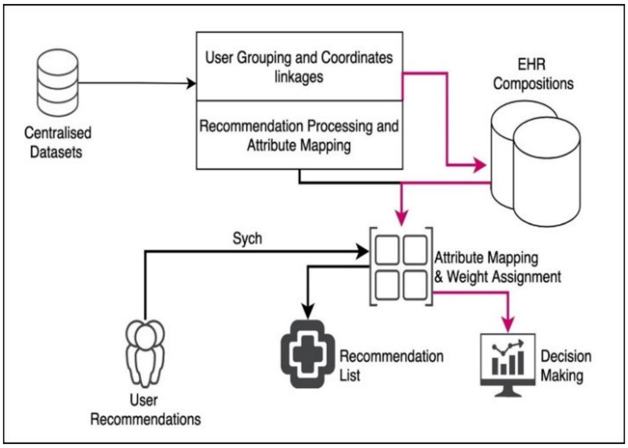

FIGURE 4. Recommendation technique for healthcare evaluation.

(θT) is computed with a fragmented validation of informative weight (w) as shown in Eq. 11.

$$D_{\theta_T} = \lim_{n\to\infty}\left(\frac{\delta\left(w_{e_{max}} \cap w_{e_{min}}\right)}{\delta s}\right).\theta T \tag{11}$$

$$\Delta w_{\theta_T} = \lim_{n\to\infty}\left(\sum_{i=0}^{n}\frac{\delta\left(w_{e_{max_i}} - w_{e_{min_i}}\right)}{\delta s}\right).\theta T_i \tag{12}$$

where 'I' is fragmented attribute of social set array of information based on keywords. Thus, the recommendation system is placed with reference to attributes values as per weight matrix shown in Eq. 11

C. NOVEL HEALTH CARE RECOMMENDATION TECHNIQUE AND DOMAIN SUPPORT

Under this system, the technique has proposed a dedicated framework for recommendation technique. The technique feature in Fig.4. The technique related dataset input from trained attributes models of user grouping and attribute mapping. These collectively project a set of EHR as $E = \{E_1, E_2, E_3, \ldots E_n\} |\forall E_i \to p_i$. where 'p' is an individual patient. The dataset then processes the attribute based on each occurrence of a client attribute with reference to w_{θ_T} as shown in Eq.12. These attributes are further processed under the framework for recommendation. Using an attributes weighting and mapping as shown in Eq. 13.

The calculation of an attribute-based metric M using a limit operation, while equations Eq.14 and Eq.15 involve the summation and intersection of attribute sets over a certain range of indices Thus, a series of attributes and mapping (M) is extracted with a ratio interdependency function as $M = (m_1, m_2, m_3, \ldots m_n)$ under each $m_i \to p_i$. Such that $\forall p_i \in E$ and $E \varepsilon F$. This inter-dependency must be evaluated as shown in Eq. 16 of recommendation (U) and user recommendation (U_R). Thus, a series of recommendations is extracted and validation for the user processing.

$$M = \int_0^{\infty} \lim_{n\to\infty}\left(\frac{\delta\,(w_{\theta T})_i}{\delta t}\right).^{\Delta T_\theta} \tag{13}$$

$$M = \int_0^{\infty} \lim_{n\to\infty}\left(\frac{\delta\,(w_{\theta T})_i \cap \Delta F_i}{\delta t}\right)_0^t \tag{14}$$

$$\forall M = \int_0^{\infty} \lim_{n\to\infty}\left(\sum_{i=0}^{n}\sum_{j=i+1}^{n}\left\{\frac{\delta\,(w_{\theta T})_i \cap \Delta F_i}{\delta t}\right\}\right)_0^t \tag{15}$$

$$R = \int_0^{\infty} \lim_{n\to\infty}\left(\frac{\delta\,(m_n)}{\delta t} \cup \Delta w_{\theta_T}\right) \tag{16}$$

$$R = \lim._{n\to\infty} \Delta u_R \cup \left[\sum_{i=0}^{n}\left(\frac{\delta\,(m_n)}{\delta t} \cup \Delta w_{\theta_T}\right)\right] \tag{17}$$

V. RESULTS AND DISCUSSION

The proposed technique has achieved reliable performance accuracy in recommending the healthcare services from various social medical platforms. The data collection is stream in Table.2 from multiple sources and attribute extracted using "Script Processing". The consideration vector of all parameters or attributes are retrieved from API based extraction.

The evaluation parameter of inter-dependent attributes extraction is the primary step for categorizing and processing the recommendation-based datasets. This data is further trained and evaluated as shown in Table. 3 and Table. 4 respectively. The attributes and spark MLIB processing with reference to delay time and processing time for customizing the user given keyword to SQL query injection is computed and recorded. The proposed system has provided us with a reliable ecosystem to approve and manage dynamic recommendations via a Controlled Learning Based Neural Networking (CLNN) model. The computational and proposed accuracy of the technique has achieved a higher order of dependency. The proposed system has served on various service categories and levels to assure the process is

$$S_i = \left[\begin{array}{ccc} S_\theta & S_\beta & S_\alpha \\ \begin{pmatrix} S_{\theta_{11}} & S_{\theta_{12}}\cdots & S_{\theta_{13}} \\ S_{\theta_{21}} & S_{\theta_{22}}\cdots & S_{\theta_{2n}} \\ S_{\theta_{31}} & S_{\theta_{32}}\cdots & S_{\theta_{3n}} \end{pmatrix} & \begin{pmatrix} S_{\beta_{11}} & S_{\beta_{12}}\cdots & S_{\beta_{13}} \\ S_{\beta_{21}} & S_{\beta_{22}}\cdots & S_{\beta_2 n} \\ S_{\beta_{31}} & S_{\beta_{32}}\cdots & S_{\beta_{3n}} \end{pmatrix} & \cdots \\ \vdots\quad\vdots\quad\vdots & \vdots\quad\vdots\quad\vdots & \cdots \end{array}\right] \tag{2}$$

$$S_i = \left\{\left[\frac{\delta\,(S_\theta) + \delta\,(S_\beta) + \delta\,(S_\alpha)}{\delta t}\right].\lim_{n\to\infty}\left(\frac{\delta\,(S_i)}{\delta t}\right)^n\right\} \tag{3}$$

TABLE 2. Script processed attributes representation.

Platform	Data Acquired mode	Script Processing Attributes				
		Dependency Matrix	Saturated Parameters	Data Feasibility	Performance Matrix	Authentication Certificate
Facebook	Posts	√		√	√	√
	API		√		√	√
	Sockets	√	√	√		
	Unauthorized		√	√	√	
Tweeter	Posts	√		√	√	√
	API	√	√	√	√	√
	Sockets		√	√	√	√
	Unauthorized	√		√	√	√
Koo (beta)	Posts	√		√		√
	API			√		√
	Sockets	√	√		√	√
	Unauthorized		√			

TABLE 3. Social media extracted patterns.

Social media	Downloaded Dataset Size (MB)	Server Response time (ms)	Training Dataset Size (MB)	Testing Dataset Size (MB)
Facebook	2341	0.834	562	212
Tweeter	3990	0.321	712	225
Koo	890	0.975	87	15

TABLE 4. Recommendation performance evaluation.

Social Media (dataset)	F1-Score	Precision	Recall	Dependency Matrix	Proposed Accuracy (%)	Computational Accuracy (%)
Facebook	2.762	88.21	92.12	82.76	89.32	91.79
Tweeter	9.23	87.23	97.21	88.12	90.11	93.90
Koo	1.32	83.82	91.65	83.32	50.21	62.02

internally evaluated with respect to the behavior patterns of keywords from users and processed via SQL Query injection processing.

The process of inclusion of social media under Facebook, Tweeter and Koo is aligned and processed with the reference to Table. 4 as the scripted processing and Hadoop distributed

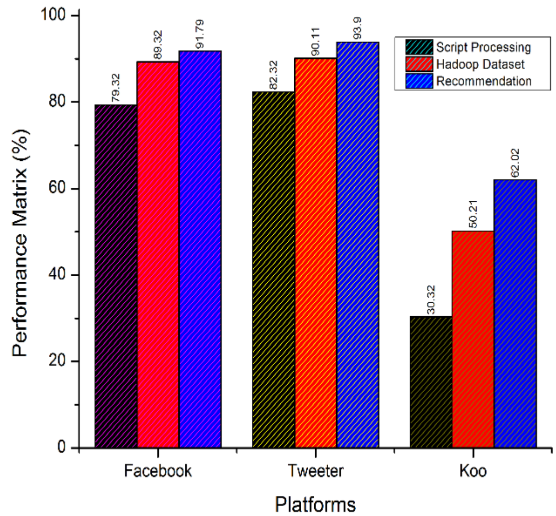

FIGURE 5. Performance estimation on recommendation techniques v/s other approaches.

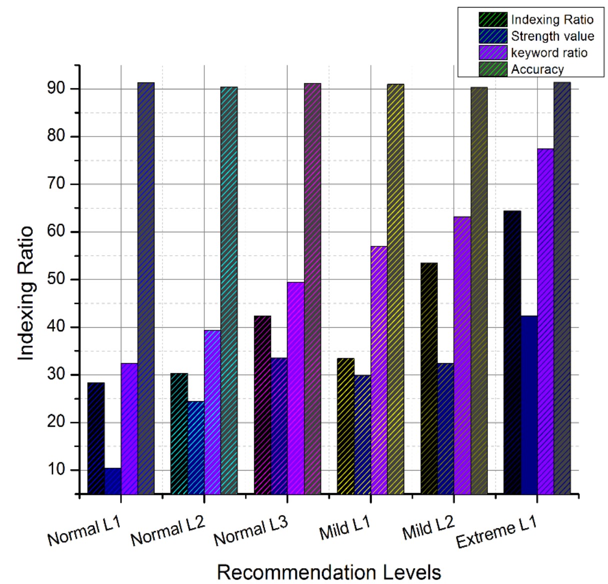

FIGURE 6. Service type categorization of larger datasets recommendations.

processing as shown in Fig. 5. The overall performance estimation with the process is relatively improved under the proposed recommendation approach. The validation is supported and contributed via the multi-variant recommendation model for processing. The dataset alignment is done using the Kaggle dataset processing.

The variations in recommendation accuracy with changing Hadoop accuracy levels are depicted in Fig-6 for each platform. This comparative analysis helps in understanding the sensitivity of recommendation systems to variations in the underlying data processing infrastructure.

The recommendation of services and the associated types are inter-chained and coordinated under the proposed recommendation technique. The normal, mild and extreme is categorized and processed under the major parameters such

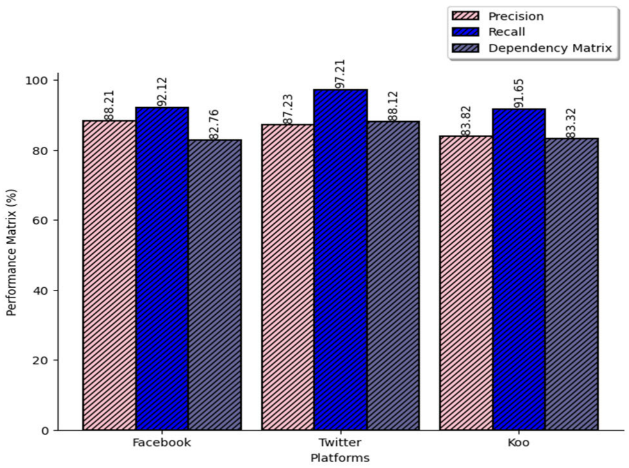

FIGURE 7. Performance evaluation of dependency matrix with precision, recall.

TABLE 5. Service recommendation accuracy matrix.

Service Type	Service Keyword	Recommendation Keywords	Accuracy (%)
Normal – L1	stomach pain, head pain, cold, fever, joint pains	Self-remedies, paracetamol, CPM, Crosin, Seradon,	92.81
Normal – L2	Sever stomach pain, joint pains, back pain, body pain	Paracetamol, penicillin, pain killer drugs, aspirin,	91.97
Normal – L3	Chronical diabetics, Blood pressure, post stroke rehabilitation, post-surgery	Exercise, yoga, ecosprin, surgical drugs, regular visits, consultation	93.92
Mild – L1	First aid, remedies, drugs recommendation	Exercise, yoga, Doctor recommendations	92.13
Mild – L2	High-sugar levels, low sugar levels	Doctor recommendations, Consultation appointments	91.88
Extreme – L1	Accident, emergency, medical emergency, priority, ambulance service	Ambulance recommendations, medical services, hospitals	94.21

as indexing ratio, strength values, keyword ratio and accuracy on the distributed environment.

VI. CONCLUSION

Based on the findings reported in this article, it is clear that harnessing auto-generated recommendations in social media platforms has considerable potential for improving user engagement and experience. The study emphasizes the relevance of user keyword-driven recommendations, highlighting the potential for personalizing material to individual tastes and interests.

The use of a specific framework for attribute extraction, supplemented with script programming, provides a systematic approach to recommendation generation. The implementation of tools such as SPARK to classify and customize distributed programming improves the efficiency and accuracy of recommendation extraction. Furthermore, using Controlled Learning-based Neural Networking (CLNN) models adds sophistication, allowing for greater depth of decision support.

The impressive suggestion accuracy of 93.90% attained with the Twitter API demonstrates the efficiency of the proposed technique when compared to other social media networks. This achievement paves the way for expanded deployment across other platforms, including Facebook, Koo, and maybe Instagram, demonstrating scalability and adaptability.

Finally, this study highlights the revolutionary power of auto-generated recommendations in social media platforms. The strategy provides a reliable solution for increasing user engagement and happiness by applying modern techniques and tools such as attribute extraction frameworks and CLNN models. Moving forward, these methodologies can be used in a variety of sectors, including e-commerce, multimedia streaming, and personalized advertising, where tailored recommendations are critical in user interaction and decision-making processes.

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