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Research on 5G User Perception Detection and Experience Improvement Optimization Based on Capsule Network

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ABSTRACT

COVID-19 caused a global public disaster as well as an economic crisis, and other challenges. The fifth-generation network, or 5G, connects practically every machine, person, and thing on the planet. We can analyse the public's opinions and sentiments connected to COVID-19 from 5G user-generated content on social media, which will eventually aid in promoting health intervention strategies and designing successful projects based on public perceptions. The BERT language model is first used to preprocess data that has been obtained from Sina Weibo. Following that, the features of the preprocessed data are chosen using a class-wise information technique. Finally, a capsule network (CapsNet) approach is used to identify the 5G user perception and experience optimization. Dynamic routing algorithm is used for optimizing the capsule network. By comparing the suggested framework's performance with certain existing approaches, its effectiveness is evaluated. Simulation results show that the proposed method is more accurate than previous approaches at identifying 5G user experiences.

KEYWORDS

5G user perception detection, BERT language model, Capsule network model, optimization technique, user experience

INTRODUCTION

In recent years, the rapid development of social networking platforms has made it convenient for people to share opinions and ideas, thus becoming an important source of data for studying various topics (Tasneem et al., 2020). With the spread of the COVID-19 pandemic, people are increasingly concerned about the security and risk issues of 5G technology. Therefore, this article aims to explore the feelings of 5G customers toward the pandemic and optimize the 5G user experience by analyzing relevant data and adopting new strategies. In this study, we chose a popular social networking platform, Sina Weibo, as a tool to investigate the feelings of 5G customers toward the pandemic. Our goal is to understand the attitudes and opinions of users toward this epidemic by analyzing the data obtained from Sina Weibo. We pre-processed the data collected from Sina Weibo. Using the

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BERT language model, we cleaned and summarized the data to ensure the accuracy and reliability of subsequent analysis. Next, we adopted the category information method to perform feature selection on the pre-processed data, in order to help us better understand and classify user opinions and ideas. In the study, we also proposed a strategy based on capsule neural networks (CapsNets) to optimize 5G user experience and perception. Through simulation experiments, we found that this strategy performs better than traditional methods in identifying 5G user experience. This provides a valuable reference for improving the 5G user experience. Finally, we also tested the performance of different deep learning models on classification problems to evaluate their effectiveness and applicability. This study explored whether the development of 5G technology related to the COVID-19 pandemic would pose risks to consumers. We hope to conduct in-depth research to determine whether there are potential problems and challenges in the speculative development of this technology. This study can help decision-makers better understand the needs and expectations of the public, thereby formulating more targeted policies and measures. In addition, optimizing the 5G user experience and perception can improve user satisfaction and promote the application and development of 5G technology. This study provides useful methods and technical references for researchers and practitioners in related fields.

The contributions made by this study are as follows:

1. Data collection method: This study collected relevant data on the feelings and opinions of 5G users toward the COVID-19 pandemic by using Sina Weibo, a widely used social network platform. This data source provided a comprehensive and diverse sample for research, which helps to better understand user attitudes and opinions.
2. Preprocessing method: This study used the BERT language model to preprocess the data collected from Sina Weibo. BERT is one of the cutting-edge technologies in the field of natural language processing, which can effectively extract semantic information from text. Using BERT for preprocessing improved the quality and availability of data, laying the foundation for subsequent analysis.
3. Feature selection method: This study used a classification information method to select the features of preprocessed data. This method can help identify the most relevant and important features of the research problem, thereby improving the accuracy and interpretability of the analysis.
4. Optimization method: This study adopted the CapsNet method to determine the optimization strategy for 5G user perception and experience. The CapsNet is an emerging artificial intelligence algorithm with strong pattern recognition and feature extraction capabilities. By applying CapsNets, personalized optimization can be carried out to meet the needs and preferences of 5G users, improving user experience and satisfaction.

In summary, the contribution of this study lies in the selection of data collection methods, application of preprocessing methods, application of feature selection methods, and exploration of optimization methods. These contributions contribute to improving the credibility and practicality of research, while providing useful methods and technical references for researchers in related fields.

LITERATURE REVIEW

The fifth-generation (5G) mobile network is a new type of global communications infrastructure with the potential to link any machines for any purpose (Márquez-Sánchez et al., 2023; L.Wang et al., 2023). There is a need for improved key performance indicators (KPIs) in 5G networks compared to their predecessors. There is considerable agreement on the importance and usefulness of KPIs (Han et al., 2020). The operator is primarily concerned with metrics like capacity, reliability, and service quality (Giachos et al., 2023). From the standpoint of the user, the most crucial criteria are round-the-clock accessibility, boundless data storage, and zero latency. However, no technology has shown itself to be capable of providing both infinite capacity and zero latency (Malik et al., 2023). Due to the many exciting possibilities and problems it brings, the next-generation mobile network has been the topic of significant research in recent years (Osama et al., 2023). Other technologies, including two-layer architecture and cognitive radio-based architectures, are vital for the next-generation network due to their remarkable performance, despite the overwhelming attention on ultra-dense networks and millimeter waves (Wijesekara & Gunawardena, 2023). Network data analytics and machine learning are two technologies that may play a pivotal role in the 5G network's backbone. Understanding user habits is one of the most efficient ways to boost 5G network speeds (Koo et al.,2023). Wireless networking and big data technologies are on the rise with the arrival of 5G and 6G networks. High peak-data rates (in the gigabits-per-second range) and the capacity to accommodate many users with very low latency make these networks a top choice (Priya & Malhotra,2023). It is possible that the speed and precision with which diseases are treated could be improved by adopting the capabilities of the forthcoming 5G networks (Ravi et al., 2023).

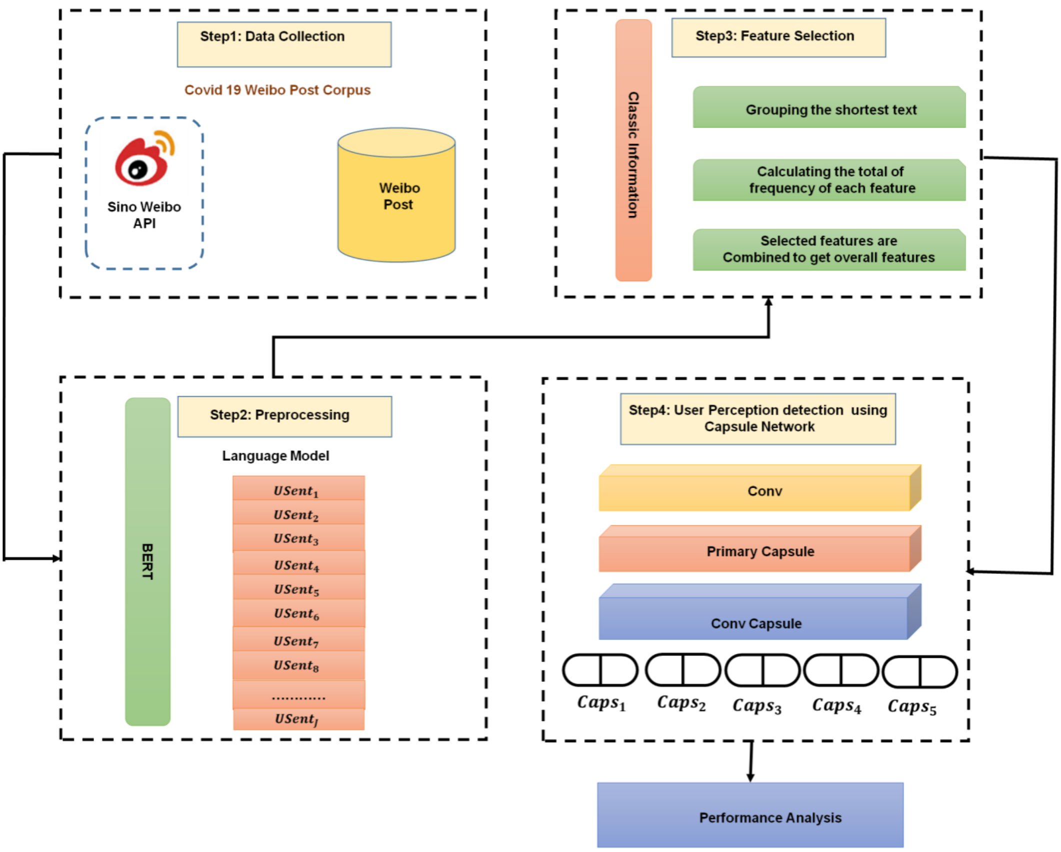
Since the advent of 4G technology, video streaming has become one of the most popular services available. This service includes popular platforms such as YouTube, Netflix, and Zoom (the videoconferencing tool). Video streaming has been accessed by 77% of Internet users, and of that percentage, around 55% enjoy video streaming via mobile services (Yang et al., 2021). The video quality of 5G is believed to be much better (Hasan et al., 2022). However, several factors beyond quality are speculated to influence the rate at which users use these services (Musa et al., 2023). This is why measuring user experience (UX) is so important. Users' emotions and reactions to a service, software, or hardware are what UX is all about (Komolafe et al., 2021). Interactivity, product feel, and the ability to serve and achieve goals, in this case, in the form of video streaming on 5G technology, are some of the main experiences that define user experiences (Angelucci et al., 2020). UX looks at the overall interaction of the user with a feature or technology.

Therefore, in this study, a UX measurement approach was carried out through a user survey regarding 4G streaming video features, which was then linked to predictions of feature usage with 5G technology (Mardian et al., 2022). The survey was conducted on a sample of the Indonesian market. The questionnaire respondents are streaming video users with 4G technology because there is no user experience with 5G technology commercially. This condition is a challenge to the research because it is necessary to create a statistical analysis model that can describe the predictive experience of 5G technology users through the results of a UX survey on 4G technology. Using this framework, the study built a structural equation model (SEM) to link both UX valuations of 4G and predictions of 5G (Dash & Sahu, 2022). The SEM that allows simultaneous testing shows the level of relationship or correlation values of the 10 factors. This structural model is an approach to providing a numerical value and not only shows the correlation value between technologies but also shows the influence of the factors that make up UX on each technology. According to the ITU-RM.0283-02 recommendation from the International Telecommunication Union (ITU), the speed of 5G technology is around 20 Gbps and the latency is only 1 ms. Besides technical specifications, 5G technology demands increased affordability and transformation of the user experience that provides innovation and solutions (Khatib & Barco, 2021). Several countries have begun to use 5G technology commercially since 2019, e.g., South Korea in 2019 and Turkey in 2020 (Cui et al., 2021).

MATERIALS AND METHODS

The goal of this research was to examine the use of CapsNet for detecting user perception and optimizing their 5G experience. The process for the suggested technique is shown in Figure 1. As a first step, information on the COVID-19 pandemic was gleaned from 5G users' Sina-Weibo posts. In order to preprocess the gathered information for further analysis, the BERT language model was used. Subsequently, we used a class-based information selection method to select the most important features. Finally, a CapsNet method was implemented to detect the 5G user experience and perception.

Figure 1. Methodology



User Experience and Quality

All customer interactions with a business's offerings (both physical and digital) are included under the umbrella term *UX*. It is more than just a matter of placement; there are many moving parts involved. What makes for a satisfying adventure is the sum of its parts, including layout, graphic design, text, brand, sound, and interaction (Chaganti et al., 2023). However, the reality is that it's easy to forget why certain features or pieces of material were included in the first place. Commonly used interchangeably but with distinct meanings, *user interface* (UI) and UX are sometimes confused with one another (Y.Wang et al., 2023). The UI design process is more concerned with the visual elements of the interface, such as the color scheme, fonts, overall aesthetics, and everything concerning branding standards.

Alternatively, UX-driven design focuses on functionality, usability, and content. Information placement is crucial. If there are too many things to do or the process is too cumbersome, consumers will often forego them. The objective is to provide consumers with only the information they need without forcing them to switch between unnecessary screens. In cases when the user is required to take action, the necessary processes can be minimized and presented in such a way that both the gathering of knowledge and its execution proceed with minimal effort. Adobe found that if images do not load or take too long to load, 39% of users will not use an interface (i.e., website or dashboard). Conversely, if the interface has been crafted meticulously, its hit rate can skyrocket.

The perspective of QoE can be formulated by combining QoS and UX. Although the QoS factor from the technical side is still considered vital, alone, it is not enough to show the satisfaction value of service users. QoS factors such as delay, jitter, loss, error, speed, and good bandwidth do not necessarily result in a high QoE value because there are additional satisfaction factors associated with users that are very subjective, diverse, and unpredictable, and these also affect UX (Afrin et al., 2017). Quality of experience is not something that exists outside of the relationship between the user and the technology. 5G technology aims to greatly enhance QoS for consumers over current 4G LTE networks by providing speeds in the gigabits-per-second (Gbps) range, latencies on the microsecond scale, and a multiplicative rise in base station capacity. There is already a noticeable pressure on existing cellular networks due to factors such as the ever-increasing ubiquity of smart devices and the launch of new emergent multimedia applications. The enhanced data speeds, capacity, latency, and quality of service provided by 5G wireless technologies are seen as the panacea for the problems now ailing cellular networks.

This report examines the history of wireless networking from its infancy to the present day, covering the advent of 5G systems as well. The protocols and multiplexing techniques of the media access control (MAC) layer, which are essential to effectively support this new physical layer, are then discussed in detail. The study also investigated "killer apps," which are thought to be the main impetus for 5G. It is significant to learn about the new QoS, QoE, and SON components that have emerged alongside the transition to 5G to have a better grasp on the enriched user experience. With the need for faster wireless connections growing, telecom companies are competing to provide the most comprehensive 5G network. It has sparked discussions on how to design and develop the most efficient and effective 5G transmitters possible, based on available technology and expertise. Virtual reality (VR) and real-world modeling tools, such as 3D maps, are useful for cutting down on the need for physical site assessments. An intuitive user experience (UX) perspective is incorporated into the design of a custom 3D map interface that aids in the discovery of complex network designs, making them more precise, straightforward, and speedy. In addition, the instrument helps in determining the optimal placement of transmitters based on the locations of users, which is an essential step in implementing 5G beamforming. In contrast to 2D maps, 3D maps make it easy to see how many stories a building has, what kind of terrain it is on, and how beamforming will help access points focus their signals where they are needed most.

While network slicing is essential to the success of 5G networks, it can be difficult to orchestrate when used to provide better performance and more affordable services to a wide range of tenants without sacrificing network slicing's unique qualities. Traffic classification, which entails keeping tabs on network activity to foresee potential demands, is crucial to ensuring a steady flow of network resources. While dynamic network slicing offers several advantages, traffic categorization is complicated by the exponential rise of traffic attributes that are not uniform. The high feature engineering and processing costs of previous machine learning and statistical studies have stymied the field. In this research, a new deep learning technique called multi-lane CapsNets was implemented to identify and classify different types of traffic in 5G network slicing. The research takes it a step further by using deep learning techniques to evaluate the model against existing literature.

Experimental Preparation

Data Collection

One of the most widely used types of social media in China is called Sina-Weibo, which can be accessed at http://us.Weibo.com (Islam & Shin, 2023). It is also often called Weibo. In 2019, Weibo had more than 516 million users actively logging in every month. This research collected Weibo posts that were connected to COVID-19. Weibo messages pertaining to COVID-19 were gathered using the keywords *pneumonia* and *coronavirus* as the search term, and the timestamps ranged from 00:00 on January 9, 2020, to 24:00 on February 10, 2020. This was accomplished with the use of Weibo's application programming interfaces (APIs). The user ID, the timestamp, the content, and the location were all pieces of information that were retrieved.

Preprocessing

The BERT language model is one that was developed by Google (Sami et al.,2023). It accomplishes the most advanced level of performance possible in a wide variety of natural language processing (NLP) activities. The BERT model that has already been trained may have its parameters adjusted to better perform various NLP tasks. The original words posted on Weibo include distracting elements. It is essential to eliminate noise and enhance the effectiveness of the word segmentation process. By using the BERT language model, very brief Weibo messages that had less than four words, as well as repeated Weibo text, were removed. After then, there were a total of 1,413,297 messages placed on Weibo, including 105,330 texts that included geographical location information. Using information from the COVID-19 Weibo posts, we fine-tuned the pre-trained “BERT-Base, Chinese” model. The vectors that are modified by such a finely tailored BERT model gain the knowledge of the COVID-19 pandemic, and as a result, they are more suited for the user perception detecting task associated with 5G.

Feature Selection

The features of the preprocessed text data were selected by using a class-wise information approach (Wen et al., 2020). The three phases that make up the class-wise feature selection approach are as follows: Firstly, the user perception class-related (UPCR) short texts were aggregated, and then the total frequency of each feature corresponding to each class was computed (Ghozali, 2023). After the weights of the feature values have been collected, they are sorted in decreasing order, and features with low weights are removed by setting the threshold value. In this case, the value of the threshold is determined experimentally, and it shows the number of features that are selected from each user perception class. These procedures were carried out with each individual class. In the last step, the subsets of features that were selected from each class were merged to produce overall features. These features are used throughout the classifiers’ following training processes as inputs.

Assume that there are l classes, each of which has i short sentences. M-dimensional term frequency vectors are used to characterize the short texts (i.e., feature vector). The structure of the term document matrix, say T of dimension $\left(li \times M\right)$, is such that each row corresponds to a brief text associated with class D_l and each column corresponds to a feature E, where

$$E = \left\{l_1, l_2, \ldots\ldots, l_M,\right\} \tag{1}$$

To begin, we calculate the frequency of each characteristic l_k belonging to class D_l, as a sum, i.e.,

$$ClassTermFrequency\left(D_l, l_k\right) = \sum_{st=1}^{i} Frequency \tag{2}$$

where Frequency $\left(T_{ts}, l_k\right)$ is the rate at which l_k features appear in T_{ts} and i is the total number of texts in D_l that are short. The resulting matrix, ClassTermFrequency $\left(D_l, l_k\right)$, will be $1 \times M$ in size for each category. In addition, we determine which words appear most often inside each class by decreasing order of ClassTermFrequency values. When threshold values are established, we may choose a subset of features, M'. Here, we use empirical analysis to choose a single threshold value. The selected features that were prioritized are addressed in Equation 3.

$$E_1^{'} = \{E_1, E_2, \dots E_M\} \tag{3}$$

where $M' < M$ and $E_1^{'}$ are features that are exclusive to a class. For each group, we follow the same pattern. In addition, we use the union function on the feature sets that we extracted from each class,

$$E' = E_1^{'} \cup E_2^{'} \dots\dots \cup E_m^{'} \tag{4}$$

As a final step, the classifiers were trained using the chosen features E'.

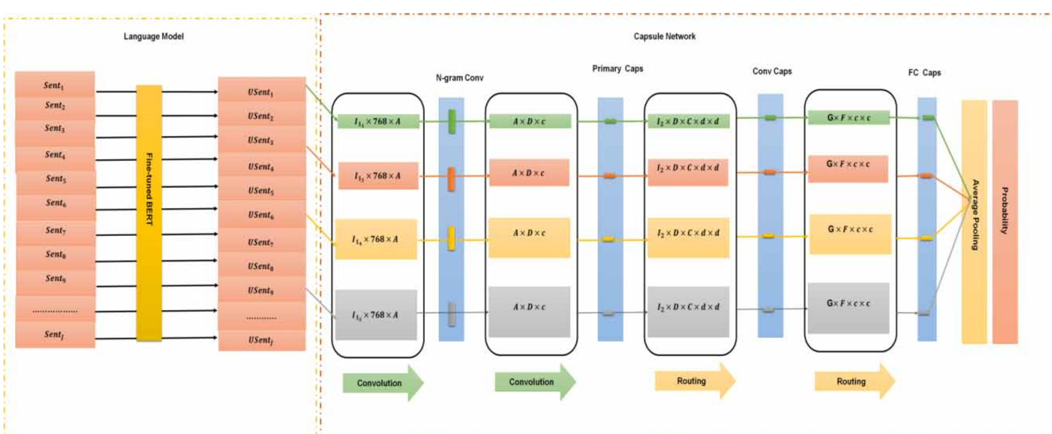
Optimization of the CapsNet Strategy

We developed a CapsNet with a receptive field that has many levels in this research. Many recent studies on CNN-dependent text categorization have used a multi-level receptive field, but only a few have tested the effectiveness of a single-level receptive field. The receptive field of size 1, a specific network architecture, has been widely employed by researchers to adjust the dimensionality of feature maps used in text categorization. When phrase vectors, rather than word vectors, are fed into a network, this concept becomes crucial. When the receptive field is set to 1, the model is at its best when learning the characteristics of a single post; when it is set to a value greater than 1, the model is at its best when learning different representations of the same user perception and correlations between different user perceptions. We introduced the multi-level receptive field CapsNet because it can learn more generalizable text features from user ratings. Five layers comprise the architecture: an *n*-gram convolutional layer, a main capsule layer, a convolutional capsule layer, a fully connected capsule layer, and a capsule average pooling layer. What follows is an explanation of the wide-grained CapsNet's many layers. Figure 2 is a conceptual illustration of a method for detecting user opinions in 5G networks.

n-Gram Convolutional Layer

The text characteristics of 5G user perceptions may be extracted from various text representations using a typical convolutional layer called the n-*gram convolutional layer*. The convolution process of the *n*-gram convolution filter is described by Equation 5.

Figure 2. Structure of 5G user perception detection mode



$$X^{m} \in \mathbb{R}^{i_{1_b}\times 768} \tag{5}$$

where I_{1_b} denotes the a-gram size $\left(a \in \left\{1,3,4,5\right\}\right)$ during window sliding over U_{sent}. U^{m} convolves along with the sentence-windows $U_{sent_{\beta:\beta+I_{1_b}-1}}$ for generating a column-wise feature map $n^{m} \in \mathbb{R}^{J-I_{1_b}+1}$. Each element generated by X^{m} is defined by Equation 6.

$$n_{k}^{m} = e(U_{sent_{\beta:\beta+I_{1_b}-1}} rX^{m} + a_{0}; \tag{6}$$

The ReLu activation function is defined by e while element-wise multiplication and a bias term are denoted by r and $a_{0} \in \mathbb{R}$ respectively. Each filter provides A feature maps represented by Equation 7 for $m \in \left[1, A\right]$ and overall $A\left(A = 32\right)$ filters with the filter windows size of I_{1_b}.

$$N = \left[n_{1}, n_{1}, \ldots\ldots n_{A}\right] \in \mathbb{R}^{\left(J-I_{1_b}+1\right)\times A} \tag{7}$$

Primary Capsule Layer (PCL)

The first layer, known as the PCL, converts the features of 5G user perceptions discovered by the convolutional process from scalar to vector output. This output format, known as the *capsule*, allowed the model to learn the characteristics of the 5G user perception from a new angle.

$$X^{A} \in \mathbb{R}^{A\times c} \tag{8}$$

Equation 8 represents the filter applied to a number of different types of sliding windows, where c is the size of the capsule (c = 16). Assigning a letter to each of the n-gram convolution's output vectors yields $N_{k} \in \mathbb{R}^{A}$. Equation 9 yields a list of column-wise capsules.

$$r = \left(X^{q}\right)^{S} \left\{N_{k}\right\}_{k=1}^{J-I_{1_b}+1} \in \mathbb{R}^{\left(J-I_{1_b}+1\right)\times c} \tag{9}$$

Equation 10 is applied to determine each capsule $p_{k} \in \mathbb{R}^{c}$ in p.

$$p_{k} = h\left(T_{k}\right), \tag{10}$$

where $T_{k} = \left(X^{q}\right)^{S} N_{k} + a_{1}, a_{1}$ means the bias term of capsule and h denotes the activation function involving nonlinear squash function defined by Equation 11.

$$h\left(T_{k}\right) = \frac{T_{k}^{2}}{1+T_{k}^{2}} \cdot \frac{T_{k}}{T_{k}}, \tag{11}$$

The capsule feature maps may be reconfigured using Equation 12 since this layer fully utilizes $D(D = 16)$ filters.

$$P = \left[p_1, p_1, \ldots\ldots p_D\right] \in \mathbb{R}^{\left(J - I_{1_b}{}^{+1}\right) \times D \times c}, \tag{12}$$

where P consists of overall $\left(J - I_{1_b}{}^{+1}\right) \times D \times c$ -dimensional vectors.

Convolutional Capsule Layer

Incorporating the child–parent connections into the capsule helps it more properly depict the hierarchical pattern of representations regarding the internal information in neural networks. Each primary capsule in the bottom layer is connected to a convolutional capsule in the top layer. In order to establish a child–parent connection, the capsules in the base capsule layer multiply the transformation matrix. The convolutional capsule layer's parent capsule is then formed via a dynamic routing method (summarized in Algorithm 1).

$$\hat{V}_{l|k} = X_l^d v_k + \hat{a}_{l|k}, \tag{13}$$

where X_l^d represents the l_{th} matrix in transformation matrices and

$$X^d \in \mathbb{R}^{I_2 \times D \times C \times c \times c}. \tag{14}$$

In our experiment, $I_2 = 3$ represents the receptive field's size in this layer, and $I_2 \times D$ displays the number of subcapsules that are related to each parent capsule. The proportion of parent capsules to which child capsules are delivered is $C(C = 16)$; w_k represents the child-capsule in the neighborhood $I_2 \times D$. The capsule's bias term is $\hat{a}_{l|k}$.

Algorithm 1. Dynamic Routing Algorithm

procedure ROUTING $\left(\hat{V}_{l|k}, o, j\right)$

for all capsules k in layer f and capsules l in layer $\left(j+1\right): a_{l|k} \leftarrow 0$

for o iterations, do

for all capsules k in layer j and capsules l in layer $\left(j+1\right)$:

$$D_{l|k} \leftarrow \frac{exp\left(a_{l|k}\right)}{\sum_i exp\left(a_{ki}\right)}$$

for all capsules l in layer $\left(j+1\right)$:

$$T_l \leftarrow \sum_k d_{l|k} . \hat{V}_{l|k}$$

for all capsules l in layer $\left(j+1\right)$:

$$u_l = \frac{T_k^2}{1 + T_k^2} . \frac{T_k}{T_k}$$

for all capsules l in layer j and capsules l in layer $\left(j+1\right)$:

$$a_{l|k} \leftarrow a_{l|k} + \hat{V}_{l|k} . u_l$$

```
end for
return u_l
```

Fully Connected Capsule Layer

In the fully connected (FC) capsule layer, the convolutional capsules are flattened into a list of capsules. These capsules expand transformative matrices.

$$X^e \in \mathbb{R}^{G \times F \times c \times c} \tag{15}$$

$$u_l \in \mathbb{R}^c \tag{16}$$

The dynamic routing technique uses the transformation matrix described in Equation 15 to create the final capsule (expressed in Equation 16). G is the convolutional capsule layer's number of capsules, and F is the task's total number of 5G user prediction classes, with $F = 14$.

Capsule Average Pooling Layer

To identify the class of 5G user perception, the outputs from the FC capsule layer enter the capsule average pooling layer, where the class probability is calculated.

RESULT AND ANALYSIS

Experimental Result

The effectiveness of a CapsNet-based method for detecting user opinions and optimizing their 5G experience is discussed below. The performance of the proposed approach is analyzed by comparing it with conventional methodologies in terms of accuracy, precision, recall, F_1-score, and computation time. Conventional methodologies used in this research are 5G HetNets, SVM-linear, and Mask R-CNN. Here:

- TP indicates user perception marked as correctly detected that turned out to be predicted correctly.
- TN indicates 5G user perception marked as wrongly detected that did turn out to be predicted incorrectly.
- FP indicates user perception marked as wrongly detected that turned out to be predicted correctly.
- FN indicates user perception marked as correctly detected that turned out to be predicted incorrectly.

Accuracy is a commonly used performance evaluation metric that measures the ratio of the number of correctly predicted samples by a classification model to the total number of samples. If the proposed method has high accuracy in classification tasks, it indicates that the method can effectively classify samples. *Precision* refers to the proportion of samples predicted to be positive by a classification model that are actually positive. Accuracy can measure how much of a model's predicted results are truly positive. High accuracy means that there are fewer false positives in the model's prediction results. *Recall* refers to the proportion of true positive samples that a classification model can accurately predict as positive. The recall rate measures the model's ability to detect positive samples. A higher recall rate means that the model can better detect positive samples and avoid false positives. The F_1-score is an evaluation indicator that takes into account both accuracy and recall. The F_1-score is the harmonic mean of accuracy and recall, suitable for evaluating the balance performance of classification models between different categories.

Figure 3 and Table 1 show the accuracy comparison of the proposed methodology with existing methodologies. Figure 3 demonstrates that the proposed methodology has greater accuracy in user perception detection than the other existing methods. The ratio of correctly predicted 5G user instances to all predicted instances is known as accuracy. It can be calculated using the formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{17}$$

The ratio of 5G user perception positive cases to all instances that were predicted to be positive is known as precision. The formula below may be used to compute it:

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

Figure 4 and Table 2 present the precision comparison of the proposed methodology with existing methodologies. As a consequence of the performance evaluation, it has been determined that the CapsNet is higher in precision rate than the other existing methods.

Figure 3. Accuracy comparison

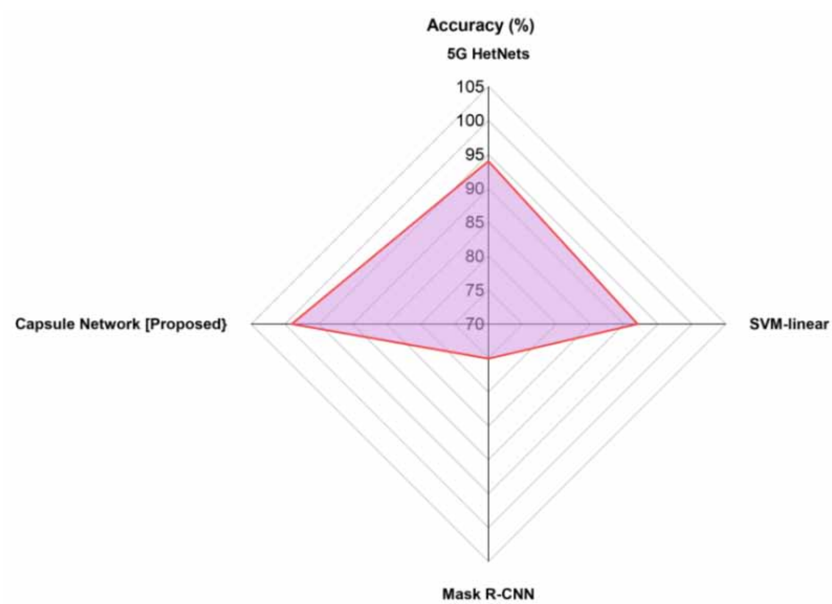


Table 1. Computation analysis of accuracy

Methods	Accuracy (%)
5G HetNets	94
SVM-linear	92
Mask R-CNN	75.1
CapsNet (proposed)	99

Figure 4. Precision comparison

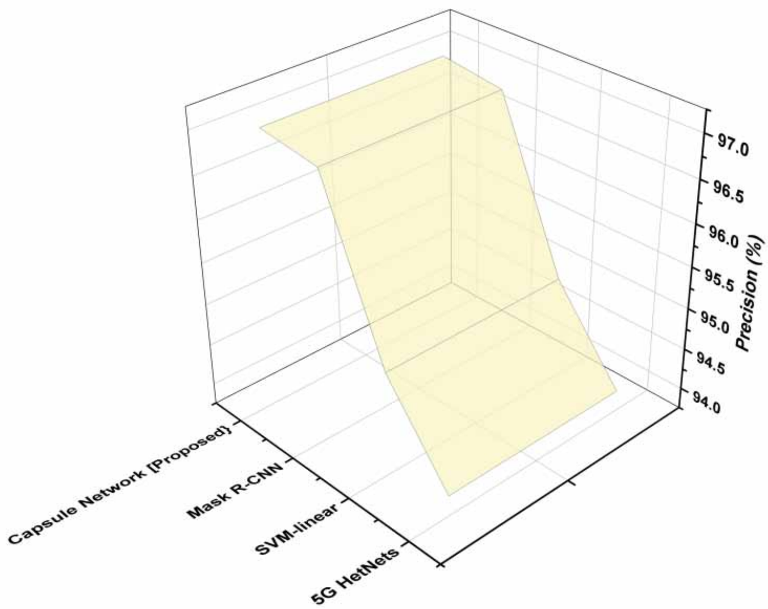


Table 2. Computation analysis of precision

Methods	Precision (%)
5G HetNets	94
SVM-linear	95
Mask R-CNN	96.9
CapsNet (proposed)	97

Figure 5 and Table 3 present the recall comparison. Figure 5 clearly shows that the recall of the CapsNet is higher than the conventional methods. It displays the proportion of occurrences of true positives 5G user perception instances with accurate labels. It may be computed as:

$$Recall = \frac{TP}{TP + FN} \quad (19)$$

The F_1-score combines recall and accuracy, and it is regarded as a proposed model's balanced and accurate performance. The harmonic mean of recall and accuracy is the F_1-score. It may be determined using:

$$F_1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (20)$$

Figure 5. Recall comparison

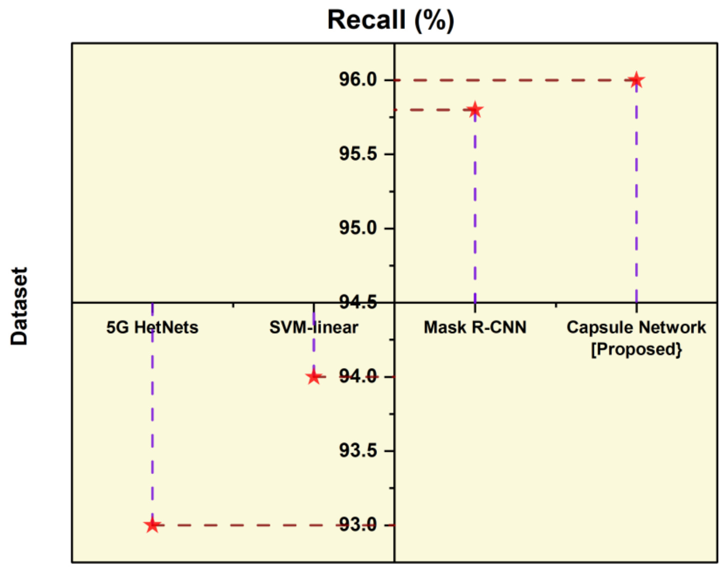


Table 3. Computation analysis of recall

Methods	Recall (%)
5G HetNets	93
SVM-linear	94
Mask R-CNN	95.8
CapsNet (proposed)	96

Figure 6 and Table 4 demonstrate the comparative evaluation of F_1-score in suggested and traditional methods. As a consequence of the performance evaluation, it has been determined that the CapsNet has a higher F measure than the other existing methods. In conclusion, the CapsNet is better than the Het Nets, SVM linear, and Mask R-CNN.

The amount of time it takes to conduct a computational operation of 5G user perception is referred to as its *computation time* (or *running time*). Figure 7 and Table 5 demonstrate the comparative evaluation of computation time. Figure 5 clearly shows that the proposed method computes lesser detection time when compared to existing methodologies.

Figure 8 shows that the Chinese public has a favorable opinion of 5G technology, particularly regarding speed, security, and performance. The frequency of positive terms in a phrase is evaluated to determine the most positive keywords toward 5G. Word count analysis reveals that the topics of speed, security, and performance get the greatest attention. Among them, people had a positive impact on their performance which is clearly shown in the figure.

The proportion of COVID-19 topics in the first level is shown in Figure 9. The most discussions (34.42%) were devoted to “opinion and sentiments.” The second most common was “government response” (16.2%), followed by “event notification” (13.94%) and “personal response” (12.82%), with similar values, and finally “seeking help” (2.01%) and reported “making donations” (1.55%).

Figure 10 provides a more in-depth examination of the distribution of subtopics. With respect to text categories, “blessing and praying” and “objective comment” dominated, with 20.89% and

Figure 6. F_1-score comparison

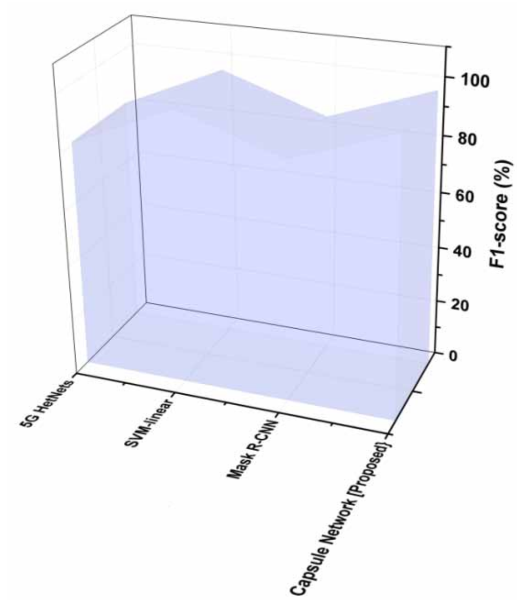


Table 4. Computation analysis of F_1-score

Methods	F_1-score (%)
5G HetNets	81
SVM-linear	97
Mask R-CNN	85
CapsNet (proposed)	98.2

Figure 7. Computation time analysis

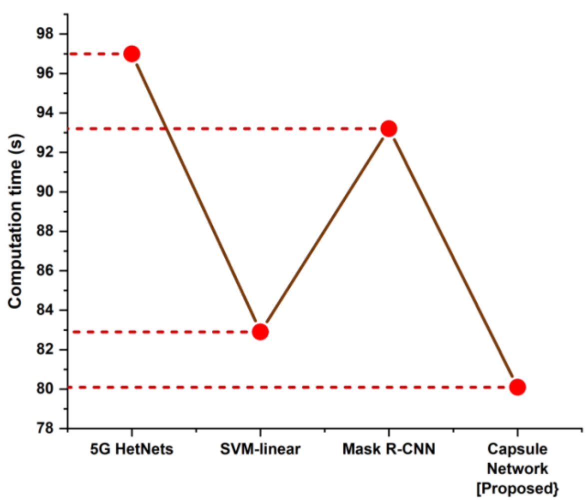


Table 5. Computation analysis of time

Methods	Computation time (s)
5G HetNets	97
SVM-linear	82.9
Mask R-CNN	93.2
CapsNet (proposed)	80.1

Figure 8. Positive trends toward the fifth generation of cellular networks (5G)

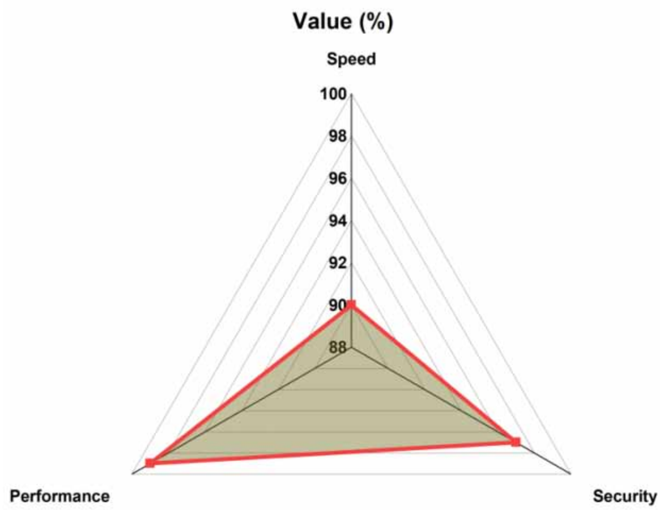


Figure 9. Classification of COVID-19-related subjects in Weibo messages

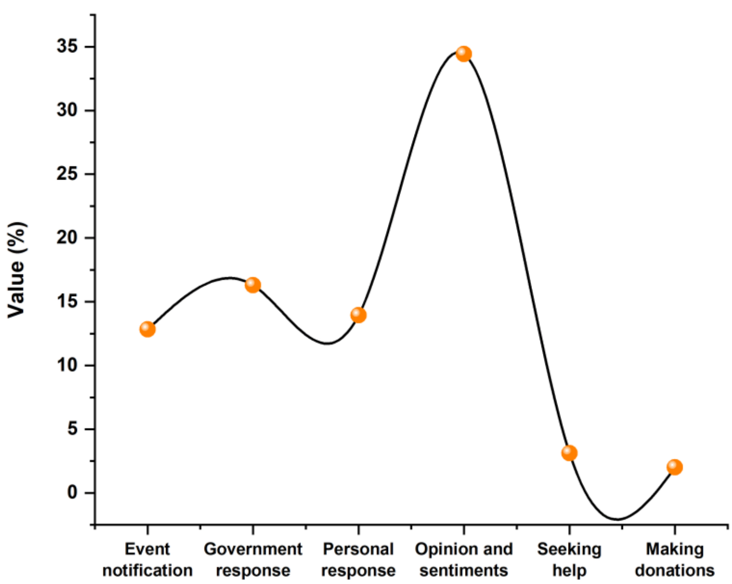
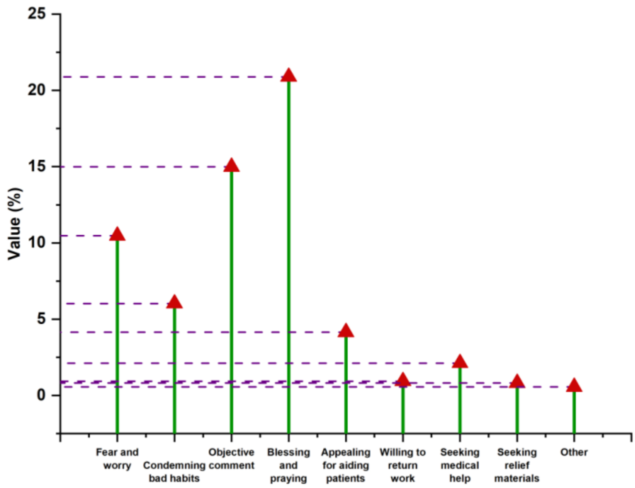


Figure 10. Classification of sub-topics in Weibo texts related to COVID-19



14.99%, respectively. “Fear and concern” accounted for 10.47%. The next most common responses were “condemning bad habits” (6.02%) and “seeking medical care” (4.14%). Less than 3% of the total was devoted to unrelated subtopics.

The CapsNet-based method has advantages over other traditional methods, mainly due to the following reasons:

1. For detecting 5G user opinions, traditional methods such as 5G HetNets and SVM-linear rely on manually designed features, while CapsNets can automatically learn and extract relevant features from text. This automated feature extraction method can help avoid bias and errors caused by improper manual feature selection.
2. In terms of optimizing the user experience for 5G, although the Mask R-CNN method can achieve accurate object detection, its computational complexity is high and running time is long. In contrast, CapsNets have lower computational complexity and shorter runtime while ensuring accuracy, making them more efficient in practical scenarios.
3. When processing text data, CapsNet-based methods can better capture the relationships and contextual information between texts, thereby improving the model’s expressiveness and generalization ability. This advantage is particularly evident when dealing with complex natural language data.
4. For extracting semantic information: Traditional methods often use shallow neural network models, which can only extract surface features in the text and cannot capture deep semantic information. As a deep learning model, the CapsNet can obtain semantic information in texts through dynamic routing mechanisms, further improving the accuracy of the model.
5. For the handling of data imbalance: In the detection and optimization of 5G user opinions, there is often a problem of imbalanced positive and negative samples. Traditional SVM-linear models may suffer from overfitting or underfitting, while CapsNets can handle imbalanced data through dynamic weight adjustment to improve the model’s generalization ability.
6. For support of multitasking learning: In 5G user experience optimization, it is often necessary to consider the evaluation and optimization of multiple indicators simultaneously. Traditional methods may require the design of multiple independent models for processing, while CapsNets

can support multi-task learning through shared parameters, improving the efficiency and accuracy of the model.

In summary, CapsNet-based methods have better performance in 5G user opinion detection and optimization. Its advantages over traditional methods mainly lie in detecting user opinions and optimizing the 5G experience, as well as in extracting semantic information, handling data imbalance issues, and supporting multitasking learning. These advantages can help improve the accuracy, generalization ability, and efficiency of the model, providing a better user experience and better services for 5G applications.

Analysis of the Application of Insights in the Real World

Today, with the gradual popularization of 5G networks, more and more users are starting to use 5G technology to enjoy faster and more stable network experiences. However, with the expansion of the 5G network scope and the enrichment of application scenarios, user perception and needs for 5G networks are also constantly changing. In order to better meet user needs and improve user experience, relevant departments need to understand user perception and insights, analyze user feedback and needs, and guide work in network optimization, application development, and policy formulation. So, how can gaining insights into 5G user perception contribute to real-world applications?

1. 5G network optimization: By analyzing user perception insights, we can understand their experience and problem feedback when using 5G networks. These insights can help operators and network equipment suppliers better understand the needs and pain points of network quality, coverage, speed, and stability. Based on these insights, relevant departments can adjust network design, improve network equipment, and optimize network deployment to provide better user experience and service quality.
2. 5G application development: By analyzing user perception and insights, we can understand their acceptance, user experience, and needs for different types of 5G applications. These insights can help developers better understand user preferences and expectations, thereby guiding the development of innovative 5G applications and services. For example, if the majority of users express interest in 5G applications in a specific field, relevant departments can increase research and investment efforts and launch more applications that meet user needs.
3. User education and support: By analyzing the user's perception and insights, it is possible to understand their level of understanding, usage skills, and problem troubles regarding 5G technology. These insights can help relevant departments develop user education plans and provide technical support. For example, if users generally express a lack of understanding or difficulty in using a certain 5G function, relevant departments can provide corresponding training and guidance to improve user technical mastery and satisfaction.
4. Policy and regulatory development: By analyzing user perceptions and insights, we can understand their concerns and opinions on 5G network construction, data privacy, security, and other aspects. These insights can provide a reference for the government and regulatory agencies to formulate relevant policies and regulations. For example, if users are generally concerned about 5G network security issues, relevant departments can strengthen network security supervision and regulatory development to protect personal information and network security.

In summary, gaining insights into 5G user perception is of great significance for real-world applications. By analyzing user experience, needs, and feedback, relevant departments can improve network design, develop innovative applications, provide user education and support, and formulate relevant policies and regulations to promote the development of 5G networks and increase user satisfaction.

CONCLUSION

Sina Weibo has evolved into a social networking platform that may be used to extract the opinions and thoughts of its users with regard to a variety of themes, as has been mentioned during the course of this work. For the purpose of this study, we used the social networking platform Sina Weibo to investigate how 5G customers feel about the COVID-19 pandemic. The data that has been acquired from Sina Weibo is first preprocessed with the assistance of the BERT language model. After that, a class-wise information approach is used in order to choose the features of the preprocessed data. In conclusion, a strategy based on CapsNets is used to determine how best to optimize the 5G user experience and perception. The findings of the simulation show that the suggested strategy is superior to conventional approaches when it comes to identifying the 5G user experience.

As part of our ongoing research, we want to determine whether or if there is a risk to consumers posed by the speculative development of 5G technology that is associated with coronavirus. In addition to this, one of our goals is to test the efficacy of a number of different deep-learning models by putting them to work on a classification problem. In the future, we can consider exploring more different deep learning models and comparing their effectiveness in classification problems. This will help further optimize and improve the identification methods for the 5G user experience. Future research can also investigate how to better promote and apply 5G networks to meet the diverse needs of users. For example, the application of 5G in fields such as healthcare, the Internet of Things, and intelligent transportation can be explored, and its impact on user experience can be evaluated.

DATA AVAILABILITY STATEMENT

The experimental data used to support the findings of this study are available from the corresponding author upon request.

CONFLICTS OF INTEREST

The author declared no conflicts of interest regarding this work.

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REFERENCES

Angelucci, A., Kuller, D., & Aliverti, A. (2020). A home telemedicine system for continuous respiratory monitoring. *IEEE Journal of Biomedical and Health Informatics*, *25*(4), 1247–1256. doi:10.1109/JBHI.2020.3012621 PMID:32750977

Chaganti, R., Suliman, W., Ravi, V., & Dua, A. (2023). Deep learning approach for SDN-enabled intrusion detection system in IoT networks. *Information (Basel)*, *14*(1), 41. doi:10.3390/info14010041

Cui, Z., Zhao, Y., Cao, Y., Cai, X., Zhang, W., & Chen, J. (2021). Malicious code detection under 5G HetNets based on a multi-objective RBM model. *IEEE Network*, *35*(2), 82–87. doi:10.1109/MNET.011.2000331

Dash, S., & Sahu, B. J. (2022). Genetic algorithm based coverage optimization 5G networks. *Journal of Information and Optimization Sciences*, *43*(5), 933–939. doi:10.1080/02522667.2022.2101212

Ghozali, M. T. (2023). Implementation of the IoT-based technology on patient medication adherence: A comprehensive bibliometric and systematic review. *Journal of Information and Communication Technology*, *22*(4), 503–544. doi:10.32890/jict2023.22.4.1

Giachos, I., Papakitsos, E. C., Savvidis, P., & Laskaris, N. (2023). Inquiring natural language processing capabilities on robotic systems through virtual assistants: A systemic approach. *Journal of Computer Science Research*, *5*(2), 28–36. doi:10.30564/jcsr.v5i2.5537

Han, X., Wang, J., Zhang, M., & Wang, X. (2020). Using social media to mine and analyze public opinion related to COVID-19 in China. *International Journal of Environmental Research and Public Health*, *17*(8), 2788. doi:10.3390/ijerph17082788 PMID:32316647

Hasan, M. K., Islam, S., Memon, I., Ismail, A. F., Abdullah, S., Budati, A. K., & Nafi, N. S. (2022). A novel resource oriented DMA framework for Internet of medical things devices in 5G network. *IEEE Transactions on Industrial Informatics*, *18*(12), 8895–8904. doi:10.1109/TII.2022.3148250

Islam, N., & Shin, S. (2023). Robust deep learning models for OFDM-based image communication systems in intelligent transportation systems (ITS) for smart cities. *Electronics (Basel)*, *12*(11), 2425. doi:10.3390/electronics12112425

Khatib, E. J., & Barco, R. (2021). Optimization of 5G networks for smart logistics. *Energies*, *14*(6), 1758. doi:10.3390/en14061758

Koo, H., Ryoo, C., & Kim, W. (2023). Simultaneous utilization of multiple radio access networks in ubiquitous 6G connectivity for autonomous ships: Opportunities and challenges. *Journal of Marine Science and Engineering*, *11*(11), 2106. doi:10.3390/jmse11112106

Malik, H., Anees, T., Naeem, A., Naqvi, R. A., & Loh, W. K. (2023). Blockchain-federated and deep-learning-based ensembling of capsule network with incremental extreme learning machines for classification of COVID-19 using CT scans. *Bioengineering (Basel, Switzerland)*, *10*(2), 203. doi:10.3390/bioengineering10020203 PMID:36829697

Mardian, R. D., Suryanegara, M., & Ramli, K. (2022). User experience of 5G video services in Indonesia: Predictions based on a structural equation model. *Information (Basel)*, *13*(3), 155. doi:10.3390/info13030155

Márquez-Sánchez, S., Calvo-Gallego, J., Erbad, A., Ibrar, M., Fernandez, J. H., Houchati, M., & Corchado, J. M. (2023). Enhancing building energy management: Adaptive edge computing for optimized efficiency and inhabitant comfort. *Electronics (Basel)*, *12*(19), 4179. doi:10.3390/electronics12194179

Musa, A. A., Hussaini, A., Liao, W., Liang, F., & Yu, W. (2023). Deep neural networks for spatial-temporal cyber-physical systems: A survey. *Future Internet*, *15*(6), 199. doi:10.3390/fi15060199

Osama, M., Ateya, A. A., Sayed, M. S., Hammad, M., Pławiak, P., Abd El-Latif, A. A., & Elsayed, R. A. (2023). Internet of medical things and healthcare 4.0: Trends, requirements, challenges, and research directions. *Sensors (Basel)*, *23*(17), 7435. doi:10.3390/s23177435 PMID:37687891

Priya, B., & Malhotra, J. (2023). Intelligent multi-connectivity based energy-efficient framework for smart city. *Journal of Network and Systems Management*, *31*(3), 48. doi:10.1007/s10922-023-09740-5

Ravi, B., Varghese, B., Murturi, I., Donta, P. K., Dustdar, S., Dehury, C. K., & Srirama, S. N. (2023). Stochastic modeling for intelligent software-defined vehicular networks: A survey. *Computers*, *12*(8), 162. doi:10.3390/computers12080162

Sami, T. M. G., Zeebaree, S. R., & Ahmed, S. H. (2023). A comprehensive review of hashing algorithm optimization for IoT devices. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(6s), 205–231.

Tasneem, N. T., Pullano, S. A., Critello, C. D., Fiorillo, A. S., & Mahbub, I. (2020). A low-power on-chip ECG monitoring system based on MWCNT/PDMS dry electrodes. *IEEE Sensors Journal*, *20*(21), 12799–12806. doi:10.1109/JSEN.2020.3001209

Wang, L., Wang, L., Zhu, Y., Chu, A., & Wang, G. (2023). CDFF: A fast and highly accurate method for recognizing traffic signs. *Neural Computing & Applications*, *35*(1), 643–662. doi:10.1007/s00521-022-07782-5

Wang, Y., Sun, M., Cui, Q., Chen, K. C., & Liao, Y. (2023). RIS-aided proactive mobile network downlink interference suppression: A deep reinforcement learning approach. *Sensors (Basel)*, *23*(14), 6550. doi:10.3390/s23146550 PMID:37514846

Wen, N., Zhang, L., Jiang, D., Wu, Z., Li, B., Sun, C., & Guo, Z. (2020). Emerging flexible sensors based on nanomaterials: Recent status and applications. *Journal of Materials Chemistry. A, Materials for Energy and Sustainability*, *8*(48), 25499–25527. doi:10.1039/D0TA09556G

Wijesekara, P. A. D. S. N., & Gunawardena, S. (2023). A Review of blockchain technology in knowledge-defined networking, its application, benefits, and challenges. *Network (Bristol, England)*, *3*(3), 343–421.

Yang, L., Yu, K., Yang, S. X., Chakraborty, C., Lu, Y., & Guo, T. (2021). An intelligent trust cloud management method for secure clustering in 5G enabled Internet of medical things. *IEEE Transactions on Industrial Informatics*, *18*(12), 8864–8875. doi:10.1109/TII.2021.3128954

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