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Analysis of the most Important Concepts Related to Social Distancing as a Result of the COVID-19 Pandemic: A Review

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Abstract

Social distance has been crucial in preventing the rapid spread of the COVID-19 pandemic since the outbreak began. Public spaces need to be safe places where an individual's social distancing is respected. Most methods of measuring social distancing consist of the following steps: the system (i) monitors and analyzes the actual distances between people in real-time; (ii) looks for violations of social distancing among the crowds; and (iii) collects information on and alerts those who violate the rules. This paper provides the first review of the substantial focus of convolutional neural networks (CNN)-based techniques. It has been conducted to identify their advantages and disadvantages. This article examines the most fundamental ideas about social distancing. The methods and knowledge of the basic algorithms used by previous researchers and studies, as well as the data set that can be used to evaluate algorithms that can tell when a distance is safe.

Keywords: Coronavirus 2019, Social Distancing, Method, COCO dataset.

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تحليل اهم المفاهيم المتعلقة بالتباعد الاجتماعي نتيجة جائحة كورونا: مقالة

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الخلاصة

كانت المسافة الاجتماعية أمرًا حاسمًا في منع الانتشار السريع لوباء COVID-19 منذ بدء تفشي المرض. لكي تكون الأماكن العامة أماكن آمنة حيث يُحترم التباعد الاجتماعي للأشخاص، تتكون معظم طرق التباعد الاجتماعي من الخطوات التالية حيث يقوم النظام (1) بمراقبة وتحليل المسافات الفعلية بين الأشخاص في الوقت الفعلي، (2) البحث عن انتهاكات التباعد الاجتماعي بين الحشود و (3) يجمع المعلومات وينبه أولئك الذين ينتهكون القواعد، توفر هذه الورقة المراجعة الأولى لـ تركيز كبير على تقنيات الشبكات العصبية التلافيفية (CNN). كما أجريت للتعرف على مزاياها وعيوبها. تتناول هذه المقالة الأكاديمية أهم الأفكار الأساسية حول التباعد الاجتماعي. منهجيات ومعرفة الخوارزميات الأساسية المستخدمة من قبل الباحثين السابقين والدراسات السابقة ومجموعة البيانات المقبولة لتقييم الخوارزميات للتعرف على المسافة الآمنة.

الكلمات المفتاحية: كوفيد -19، التباعد الاجتماعي، طريقة، مجموعة البيانات.

Introduction

Governments created regulations to restrict transmission in response to the coronavirus disease 2019 (COVID-19) pandemic. These laws culminated in 'lockdown' measures, which in many countries involved remaining at home and keeping a physical or (social) distance, between March and April 2020 [1]. The policy reaction has far-reaching implications for the health and well-being of populations across all societal sectors and health determinants. To prevent contracting diseases such as COVID-19, physical separation entails maintaining a space of at least 6 feet between persons [2]. Earlier in the epidemic, when many individuals stayed at home to limit the transmission of the virus, the phrase "social distance" was used [3]. Utilizing social and physical distance to maintain physical space in public settings to combat disease transmission is desirable [4]. Social distance is a public health technique designed to reduce the likelihood of disease transmission by keeping sick individuals from coming into close contact with healthy individuals [5]. It may include large-scale measures, such as canceling group events or restricting access to public locations as well as individual measures such as masking.

The purpose of social distancing in the case of COVID-19 is to postpone the spread of the epidemic, reduce the risk of infection among high-risk populations and alleviate the burden on health care institutions [6]. In Sections 2 and 3, we described the difficulties of practicing social distancing amid a coronavirus pandemic and strategies for dealing with the epidemic scenario. sections 4 and 5, learning techniques and their role in social distancing and dataset using in the topic of social distancing; section 6, previous studies of social distancing; and concludes the paper .

Difficulties of Practicing Social Distancing Amid Coronavirus Pandemic

Challenges or difficulties lie in the lack of human awareness of diseases and prevention methods. Social distancing has been the best human solution since ancient times, but the difficulty is in how society accepts distancing. As in the COVID-19 pandemic, the first step should be complete isolation of areas when conducting research and identifying the nature of the disease and how it spreads Several methods of protection have emerged [3]. Figure (1) shows the most critical challenges facing social distancing in terms of the person.

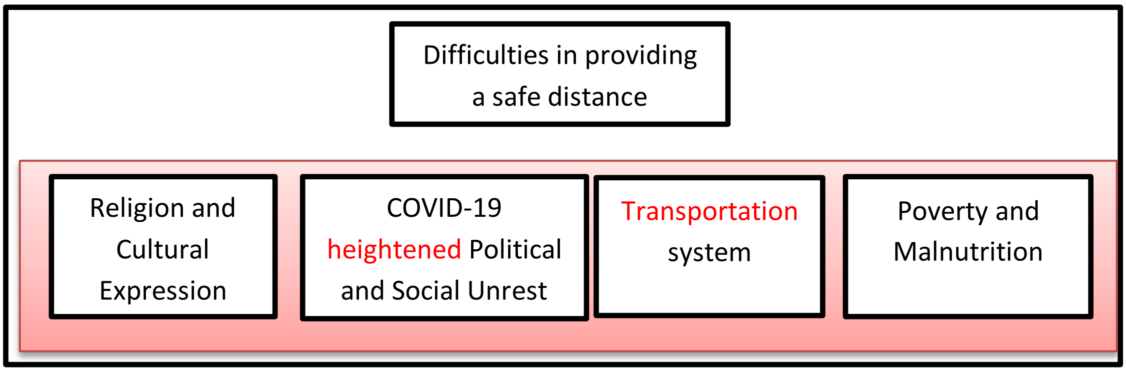

Figure 1: Difficulties in providing a safe Distance [5].

Challenges to social distancing include religious, cultural, and social interactions. COVID-19 influences religious and cultural activities in numerous ways through the cancellation of national and international artistic and cultural events. Certain countries and towns have ignored social distancing. Some countries have issued new guidelines about burial ceremonies, cultural maturity, and ritual activities, among others. Maintaining social separation is especially critical when there is a lack of information about the seriousness of fast-spreading diseases. Ongoing national lockdowns without food relief exacerbate economic and social instability and create tension between ordinary citizens and the authorities. As a result, low-income households are vulnerable to social exploitation. This can result in human rights violations, social instability during epidemic, and abuse [6].

Therefore, government help is necessary. Despite the positive aspects of social distancing, the techniques of complete isolation have adverse effects on the military and police forces as well as lessen the impact of the absolute closure and economic collapse. Therefore, there is an immediate need to implement social and preventive. Due to the partial reopening of some metropolitan areas in some big countries, the chance of re-emergence is beginning. Public transportation has become a significant risk factor for the transmission of COVID-19. There is increased likelihood of infection when using public transportation, and yet fewer people in low-income countries can afford private transportation. Instructions issued to transport operators specify that: they sanitize the interiors and exteriors of their vehicles, limit the number of passengers per vehicle, record passenger information for contact tracing, and require passengers to wear masks[4].

However, these regulations are rarely adhered to due to a lack of commitment to standards, practice, and social distance, public transportation has become a significant risk factor for the transmission of COVID-19. Due to ongoing partial closures and the number of companies, particularly in the tourism, manufacturing, aviation, and transportation industries, that have reduced production and closed businesses, many families in lower-income groups are at risk of food insecurity [2]. Due to the social economic issues generated by the COVID-19 epidemic, these earnings have led to cutbacks, job losses, increased family expenditures, and unpaid leave. As a result, families are compelled to find alternative means of subsistence while breaking COVID-19 preventative measures. These challenges have been faced worldwide because of the spread of the Corona pandemic since the beginning of its appearance and its continuation to this day. Still, 2020 and 2021 witnessed the emergence of an awareness of these factors, which was dealt with in part by human distancing [3].

Strategies for Dealing with the Epidemic Scenario

Isolation is an ancient yet highly successful approach used by humans to combat infectious illness epidemics. Infectiousness is the essence of a contagious disease outbreak. It can be spread as follows [4] [3]:

- directly
- indirectly
- indirectly from one individual to one or more individuals.

If a disease-carrying individual cannot infect more than one individual, the sickness will eventually disappear. Although each infectious disease, such as SARS and MERS, has distinct characteristics, prevention and control involve three aspects[7]:

- infectious agent.
- transmission route.
- vulnerable population.

There are three essential elements to isolation [3]:

- identify and manage the infection's source.
- sever the transmission channels.
- protect the most susceptible populations.

In China, the authorities took drastic measures to impose medical isolation on patients and close contacts, cancel public events, mandate the use of masks and frequent hand washing, and even halt traffic. The cities like Wuhan, where the source of the illness was concentrated, implemented tight control measures, while other cities and provinces thoroughly screened and isolated exporting cases. Interestingly, the places and regions discovered using isolated exporting responded positively and quickly in terms of cooperation with the restrictions [8]. Individuals' mobility between regions was likewise strictly controlled. For example, one family member was allowed to go out every two days to purchase necessities; in public places, the distance between individuals in a line had to exceed 2 meters; contactless delivery was also permitted for express delivery and takeout [9]. According to studies, social distancing strategies were most effective at the beginning of April, when many returned to work. This reduced the median number of infections by 24% by mid-2020 and 92% by the end of 2020 [10].

Learning Techniques and Their Role in Social Distancing

To choose a classifier method, you must consider both the problem you wish to answer and the characteristics that best characterize it. The mix of classifier and feature selection will ultimately improve classification accuracy. Deep learning algorithms have shown promising results in various domains, including speech recognition, computer vision, and natural language processing. The primary advantage of the deep learning approach is that it does not require a precise feature extraction stage that requires human expertise. Instead, deep learning models use their vast data-learning capabilities and flexible processing architectures to automatically and implicitly extract features [11]. This includes identifying the disease and determining the stages of sleep. In the case of social distancing, the role of algorithms and deep learning methods has a significant impact. Estimating safe distances between humans appeared became crucial at the end of 2019 due to the Corona pandemic. The beginning of its development was very noticeable, as was the scope of its application through algorithms. The detection of deep learning is extensive [12]. Table (1) shows the most famous algorithms researchers have adopted to determine and estimate safe distances between humans.

Table 1: The most Important Algorithms used in Social Distance.

RF.	Algorithm	TYPE	Classification scope	Detection scope	Description
[13]	SVM	ML	✓	☒	It is a supervised machine learning model that applies techniques to two-group classification problems. After receiving sets of labeled training data for each category, an SVM model can distinguish between categories.
[14]	LSTM	DL	✓	☒	Deep learning networks utilizing long-term, short-term memory recurrent neural networks (RNNs) can comprehend long-term dependencies, especially in sequence prediction problems.
[11]	CNN	DL	✓	☒	Convolutional Neural Network (ConvNet/CNN) is a deep learning algorithm that can receive an image as input, assign importance (learnable weights and biases) to distinct aspects/objects in the image, and distinguish between them.

[15]	YOLOv2	DL	☒	✓	A brand-new network architecture was implemented, deleting the complete connection layer and batch normalization. By adding batch normalization to all convolutional layers in YOLO to increase performance, a gain of over 2% above mAP was realized. In addition, a classifier with a high resolution was employed for training. The resolution of the classifier has been increased from 224 to 448. when transitioning to detection, the network must concurrently switch to object detection learning and the new input resolution. Using Anchor Box and DarkNet-19 as its model architecture, YOLO v2 also improves the accuracy and performance of multi-object identification.
[16]	YOLOv3	DL	☒	✓	As a result of the development and optimization of YOLOv2, YOLOv3 was created. Object detection has been discovered as a deficiency in the YOLO v3 algorithm. YOLOv3 utilizes logistic regression. The YOLO v3 algorithm divides the input image into small SS grid cells. If an object falls within a central grid cell, the cell must detect it. B bounding boxes each cell estimates the position information and objectivity scores of the distances . According to this approach, the confidence score should be 1 if the bounding box encompasses an object with greater-known ground accuracy than the previous bounding boxes and employs a significantly more complicated DarkNet-53 model backbone.
[17]	YOLOv4	DL	☒	✓	YOLO v4 is a one-stage object identification method that expands upon YOLOv3 by incorporating several additional toolkits and modules. The following section explains the utilized approaches and modules. Optimizing the train's performance to achieve a higher FPS is possible
[18]	YOLOv5	DL	✓	✓	As a PyTorch implementation rather than a Darknet clone, YOLO v5 is distinguishable from its predecessors. YOLO v5 has the same CSP backbone and PA-NET neck as YOLO v4. The most notable enhancements are the enhancement of mosaic data and the automatic learning of bounding box anchoring. This expedites training on the example problem, and batch inference (which the implementation performs by default) produces real-time results.

Relying on Table (1), the importance of the algorithm can be summarized:

SVM[13]: Is a supervised machine learning technique that may be applied to classification and regression problems. However, its primary application is in categorization difficulties. In the SVM algorithm, each data item is represented as a point in n-dimensional space (where n is the number of features), with the value of each feature corresponding to a specific coordinate. Then, perform classification by locating the hyperplane that best distinguishes the two classes.

LSTM[14]: These networks are recurrent neural networks that can learn order dependence in sequence prediction issues. Complex problem domains, such as machine translation and speech recognition, require this behavior. LSTMs are a difficult subfield in deep learning.

CNN[11]: ConvNet is a neural network that processes data with a grid-like architecture, such as an image. A digital image is a representation of visual data in binary form. It has a sequence of pixels arranged in a grid, together with pixel values indicating the brightness and hue of each pixel. The human brain analyzes a vast amount of information the instant a picture is perceived. Each neuron's receptive field is interconnected with other neurons, so the total visual field is covered. In the biological vision system, each neuron responds to inputs only in the confined region of the visual field known as the receptive field; similarly, each neuron in a CNN processes data only in its receptive field. The layers are structured such that simpler patterns (lines, curves, etc.) are detected first, followed by more complicated patterns (faces, objects, etc.). By using a CNN, computer vision can be enabled.

YOLO v2[15]: You-only-look-once (YOLO) v2 employs a single-stage network for object detection. YOLO v2 is more efficient than other two-stage deep learning object detectors, including regions with convolutional neural networks (Faster R-CNNs). YOLOv2, or YOLO9000, is a real-time object detection model with a single stage. It improves upon YOLOv1 in several areas, including using Darknet-19 as a backbone, batch normalization, a high-resolution classifier, and anchor boxes to forecast bounding boxes and running a deep learning CNN on an input image to provide network predictions. The object detector decodes the forecasts and creates bounding boxes.

YOLO v3[16]: You Only Look Once, Version 3 (YOLOv3) is a real-time object detection system that recognizes specific items in movies, live feeds, and photos. The YOLO machine learning algorithm detects an item using features learned by a deep convolutional neural network. Joseph Redmon and Ali Farhadi invented versions 1-3 of YOLO, and version 3 of the YOLO machine learning method is more accurate than the original ML algorithm. YOLOv3 is an enhancement of YOLO and YOLOv2.YOLO is implemented with the deep learning packages Keras or OpenCV.

YOLO v4[17]: This fourth version was introduced by Alexey Bochkovsky et al. in April 2020. The primary objective of this approach was to create a rapid object detector with great precision. Object detector topologies typically consist of multiple components. They optimized this architecture and employed the most recent version of YOLO, YOLOv3, as the last object detector in the chain.

YOLO v5[18]: This is an object detection algorithm that divides images into a grid system. Each cell in the grid is responsible for detecting objects within itself.

Dataset Using in the Topic of Social Distancing

Numerous datasets on the discovery of image objects have been compiled to advance relevant fields. Throughout the history of object identification research, data sets have played a crucial role as a common platform for evaluating and comparing the performance of competing algorithms and advancing the field by posing increasingly demanding challenges. Notably, deep learning techniques have recently achieved tremendous success for a variety of visual recognition problems; large amounts of annotated data and Internet access to a large number of images enable the creation of comprehensive data sets that capture the immense richness and diversity of objects [19]. The following are prominent datasets for generic object detection.

Pascal VOC benchmark [20]: 2005 to 2012

It includes 20 object categories, such as people, domestic, animals, pets, vehicles, airplanes, bicycles, boats, trains, bottles and home furnishings. Each image in this dataset is segmented at the pixel level, has a bounding box, and is annotated with the item class. This dataset has been used extensively as a standard for object detection, semantic segmentation, and classification tasks. The PASCAL VOC dataset consists of three subsets: 1,464 training images, 1,449 validation images, and a private testing set. It used low levels of social distancing.

ILSVRC (Image Net large-scale visual recognition challenge) [21]: 2010-2017

It refers to large-scale object identification and picture classification algorithms. A high-level objective is to enable researchers to compare progress in detection across a broader spectrum of objects using the costly labeling process. The second goal is to assess the development of computer vision for large-scale image indexing, retrieval, and annotation. It used medium levels of in social distancing

COCO (Common Objects in Context) [22]: 2015-2021

It is a large-scale dataset for object identification, segmentation, and annotation. It used a high level of social distancing. COCO has numerous attributes:

- ✓ object segmentation
- ✓ recognition in context
- ✓ superpixel stuff segmentation
- ✓ 330K images (>200K labeled)
- ✓ 1.5 million object instances
- ✓ 80object categories
- ✓ 91 stuff categories
- ✓ five captions per image
- ✓ 250,000 people with critical points

VisDrone2019 benchmark [23]: 2018-2022

Includes properly annotated ground-truth data for various essential computer vision tasks intended to provide drones with vision. The AISKYEYE team collects the VisDrone2019 dataset at Tianjin University, China's Machine Learning and Data Mining Lab. The benchmark dataset consists of 288 video clips containing 261,908 frames and 10,209 static images captured by various drone-mounted cameras, covering a wide range of aspects including location (taken from 14 different Chinese cities separated by thousands of kilometers), environment (urban and rural), objects (pedestrians, vehicles, bicycles, etc.), and density (sparse and crowded scenes). Note that the dataset was collected using a variety of drone platforms (i.e., different drone models), in various scenarios, and under varying weather and illumination conditions. Over 2.6 million bounding boxes depicting regularly occurring things such as pedestrians, automobiles, bicycles, and tricycles are manually identified on these frames. Furthermore, scene visibility, object class, and occlusion are provided for improved data utilization. It used a low level of social distancing.

Google Open images V5 [24]:(2016-2019)

Includes segmentation masks for 2.8 million instances of objects in 350 categories. In addition to the masks, they added 6.4 million new human-verified image-level labels, bringing the total number of labels to 36.5 million over roughly 20,000 categories. This dataset is ideal for constructing object detection models. It used a low level of social distancing.

Pedestrian detection dataset [25]: (2007)

It contains photos used for pedestrian detection in the reported studies. The photographs were taken on campuses and on urban streets. In these photographs, the subjects of interest are pedestrians. Every picture has at least one pedestrian. In this database, the heights of tagged pedestrians lie within [180,390] pixels. All pedestrians are facing forward. There are 170 photos, including 345 tagged pedestrians, of which 96 were captured near the University of Pennsylvania and 74 were taken near Fudan University. It has a medium level of social distance. Below is Figure (2), types of the dataset used in social distancing.

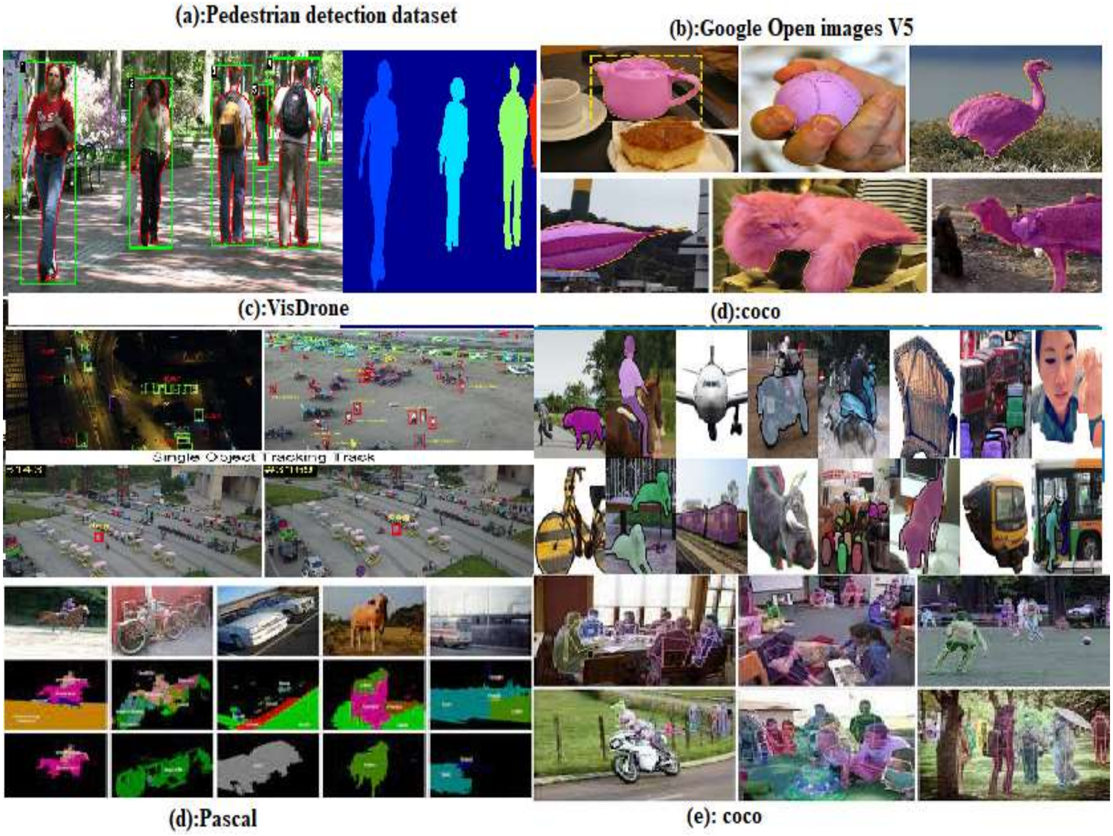

Figure 2: Sample of Images Belonging to a Famous Dataset.

Previous studies of social distance

The following Table (2) shows some previous studies with promising results in the field of estimating the safe distance for the prevention of the Corona pandemic.

Table 2: Previous Studies of Social Distancing

Year and no. of references	Advantages and disadvantages	Performance	Dataset
2020 [26]	• They developed a Deep Neural Network (DNN) model based on computer vision and YOLOv4, an updated inverse perspective mapping (IPM) with the SORT tracking algorithm and CCTV security cameras. • It did not include industrial applications, such as pedestrian detection for driving automation autonomous vehicles.	Accuracy 99.8% FPS 24.1	MS COCO Google Open Image datasets

2020 [27]	• They use a mobile robot with commodity sensors by using Robot's RGB- camera commodity sensors, /or a CCTV camera, or thermal camera. • Additional detection methods, including mask and body temperature detection, need to be integrated into the pedestrian recognition algorithm, as well as the ability to increase the computing power of the hardware and calibrate the camera's perspective view.	It can efficiently track a pedestrian walking at 0.75 m/sec.	Manually collected dataset.
2021 [28]	• Used YOLOv3 over real-time by CCTV surveillance camera. • To prevent Coronavirus transmission in the containment zones, it will be necessary to test the complete system to check up on a big crowd. A crowd density detecting system will be added to monitor the public's population.	mAP 51%	Oxford Town Center data
2021 [29]	• They conducted a comparative analysis of a model pre-trained for detecting the presence of an object and using Raspberry Pi and Camera pi. • They should anticipate enhancing their deep learning model by taking 3D scenarios into account.	FPS 1,1	PASCAL (VOC0712). COCO
2021 [30]	• They used Faster-RCNN for person detection in the photos and transferred learning approaches to enhance the framework's overall efficiency. Also used IP cameras. • Faster RCNN is a two-stage detector that localizes before classifying. This method is slower than one-stage detectors, such as YOLO, which perform both functions in a single stage.	Accuracy 96 % False Positive Rate 0.6%.	MS-COCO
2021 [31]	• They use two successive CNN models to detect a person's location in an image and a CCTV camera. • There is no indication of the algorithms that were employed.	Model 1 Accuracy 97% Model 2 Accuracy 98.5%.	Manually collected dataset

Conclusion

Social distancing has long been regarded as a strong defense against the development of dangerous illnesses like COVID-19. Not only does it put a strain on patients and healthcare systems, but it also pushes the entire world into serious financial loss. This review proposes quick and practical approaches for tracking social distance using deep learning models and object identification. This review aimed to work on the concept of safe distance and its importance in avoiding infection with the epidemic, identify some algorithms that previous researchers used, and identify the most famous types of data sets through which the quality of systems performance is evaluated, It also aimed to identify the most critical research which is highly cited by researchers where research results were within the range of 90 percent.

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