Multimedia Tools and Applications (2024) 83:4409–4442
https://doi.org/10.1007/s11042-023-15355-4

Big health data for elderly employees job performance of SOEs: visionary and enticing challenges

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Received: 17 April 2022 / Revised: 25 October 2022 / Accepted: 15 April 2023 /
Published online: 25 May 2023

Abstract

The method is providing and overview of the organization in the management perspective, within the health big data analysis, especially for the elderly employees, the organizations could sign the elderly employees within the right tasks, it reducing the costs by increasing the employees' job performance and organization performance. By addressing the importance role of big health data analytics (BDHA) in the healthcare system .moreover BDHA enables a patient's medical records to be searched in a dynamic, interactive manner. One billion records were made in two hours. Current clinical reporting compares large health data profiles and meta-big health data, giving health apps basic interfaces. A combination of Hadoop/MapReduce and HBase was used to generate the necessary hospital-specific large heath data. One billion (10TB) and three billion (30TB) HBase large health data files might be created in a week or a month using the concept. Apache Hadoop technologies tested simulated medical records. Inconsistencies reduced big health data. An encounter-centered big health database was difficult to set up due to the complicated medical system connections between big health data profiles. Associated with job performance such as the gender, current/past job positions and the health conditions are important. For genders the 66.36% of respondents in the experiments are females, 33.64 are males, majority of are healthy which are 66.97%, 30.58% are common geriatric disease, rest 2.45% are suffering from occupational disease; In terms of the current/past job positions, 20% of the respondents are working as accountant, followed by sales and management level. The Diagnostic and Statistical Manual, lists 157 distinct illnesses. Individuals may be diagnosed with one or more illnesses as a consequence of medical health professionals watching and analyzing their symptoms. It has been discovered that mental health issues have a negative impact on employees' job performance. For example, research on individuals with anxiety and depression has a direct impact on concentrations, decision-making process, and risk-taking behavior, which can be determined for job performance. Machine learning focuses on approaches that can be used to create accurate predictions about future characteristics based on previous training and post training. Principles such as job task and computational learning are crucial for machine learning algorithms that use a large amount of big health data.

Keywords Big health big health data · SOEs · Job performance · Patient pattern

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1 Introduction

In the last few years, the COVID-19 crisis has made health information systems pay attention due it has had a big impact on social and economic conditions, which is expected to generate a lot of credibility on health. Many health management and experts believe that this big health data can easily discover significant information to improve health policy, improve patient safety, reduce redundancies and costs, and fit in despite the health challenges. Furthermore, can use infixing and fitting the aging population. There is a larger requirement for action and enterprises in productivities. The purpose of this study is to look into health data, the challenges and solutions for big health data analytics, such as extracting information from collections of health data and fitting it into models for aging societies and job performance in relation to the cost of physical parameter by re-assigning them to new jobs or re-organization within an organization. Health data analytics aims to evaluate a pipelined current framework for use as a guideline or reference in health care. The role of big health data in leveraging healthcare system data is expanding. It enables interactive, dynamic searches on exceedingly large and varied collections of patient health data to match them with extensive human recourse productivity to improve the platform's big health data visualization capabilities. As a consequence of our partnership with Compute China/Medical System Platform Health Authority, we have built a BIG Healthcare big health data platform BDHP. BDHP is a healthcare big health data platform. They created an emulation of the primary hospital system's big health data to demonstrate the framework's capabilities. Current clinical reporting was used to cross-reference big health data profiles and meta-big health data. Various Apache Spark applications, including Zeppelin and Jupiter web-based interfaces, as well as Apache Drill interfaces, were used to examine multiple patient query types utilizing big health data fed into the Hadoop file system. This portal will link and enroll the whole mainland Chinese population. It could only perform basic searches and had a limited number of visualizations, making it useless in the healthcare field. Searches, on the other hand, have a restricted number of visualizations, rendering them useless for healthcare. It provided simple interfaces for health applications, but its interface tools limited versatility, and it required additional setup time before running queries. The feasibility process is based on performing all queries in parallel with excellent usability, using our BDHP platform with high performance stacks, as well as in unison, allowing us to run all queries in parallel throughout our HBDA platform. New technologies that influence patient big health data need extensive technical testing before being used in many hospital systems. Hospital was used to portray a simulation of patient big health data, which was then cross-referenced with existing meta-big health data profiles over then billion patient records are stored in the no SQL big health database (HBase), which was constructed, indexed, and saved on the test cross-platform utilizing the Hadoop Distributed File System (HDFS). Hadoop/MapReduce and HBase (key-value NoSQL big health database storage) were utilized to establish an interactive big health data Platform (BDA) that generated the required hospital-specific information in massive quantities. The framework needs a week or a month to create one billion (1000TB) or three billion (3000TB) HBase big health data files. In further performance tests, Apache technologies from Hadoop's ecosystem were employed to extract conclusions from simulated patient information. Over hundreds of cycles, HDFS ingestion with big health database integrity was protected via to HBase. The bulk loading from MapReduce to HBase took a month to finish. HBase inconsistencies hampered the ability to quickly produce and transfer big health data to HBase. In the period of China's ageing society, big health database-based hospital systems were difficult to adopt the fitting model to affect the health of the total productivity of labor to enhance the economy, and the big health data profiles properly represented the subtle nature of patient-hospital interactions. As a result of our platform, many healthcare companies will be able to uncover new big health data solutions that might improve their operations.

In this research we utilizing a big health data platform fitted to the management level of a private organization to build to simulation functionality and performance, employing Hadoop/MapReduce technologies distributed over HBase (key-value NoSQL big health database storage) and creating hospitalization meta-big health data. Meanwhile, in the management point of view, by using this method, it can maximize the benefits for the organizations, especially, for the elderly employees group, through the method, the organizations can signing the rightful employees with the "proper" tasks according to their health conditions, it can reducing the cost while increasing the employees' job performance, resulting the increasing the organizational performance as well.

To implementing an enterprise model based on the data extracted for encountering the activities of a selected enterprise, and matching them with medical records proved very challenging due to the complicated linkages between large health data profiles in a medical system. We will preserve an employee's behavior and records throughout his career in order to assess vast amounts of knowledge, health, and future position based on the connection, despite key-value storage suggestions that are memory intensive.

2 Research background

Adapting a model from an abstract health data level to practical and real-life problems such as labor shortages, and the lack of experience that will be repeated by researching the sitting studies in the fields of big health data, and big health data management, contracting a model to practical and real-life problems reused the expert labor due to the lack of experience that will be repeated by researching the sitting studies (It will more costly to train an expert, hence the process is more costly) in the fields of big health data, and big health data management.

2.1 Big health data

2.1.1 Big health data source

The researchers are the one benefit from the improved value, and raw big health data is made available to them in a variety of forms, such as features and videos caption for their evaluation. Due to big health data must be kept in a value-added state, it is common for it to be transformed from one format to another. According to, there is no standard or widely accepted way for storing raw big health data for big health data and code, as well as the parameter choices that resulted in that information. Any big health data life cycle typically begins with the generation or big health data collection phase, which is the first and most fundamental stage in the process. A tremendous amount of information was recorded as a consequence of searches, chat logs, micro-biology posts, and online forum chats. People's daily lives are intricately intertwined in this information era, and they share traits such as high value and low density, among others. Individual Internet big health data is not necessarily useful in some cases. The detailed analysis and collection of massive volumes of big health data enables the discovery of critical information such as user habits and interests. The capacity to predict human behavior and emotions is a possibility.

2.2 Content organization

Massive volumes of big health data might be unstructured, semi-structured, or sorted information. A relational big health database management system (RDBMS) manages and queries structured big health data recorded in a big health database as records, which employs structural programming languages such as SQL to accomplish. Semi-structured big health data includes, among other things, XML big health data, records, words, and other components [2]. Tables are used to store big health data instead of utilizing a regular big health database [29]. As a result, collecting semi-structured big health data necessitates the use of complex rules that dynamically adjust the next action in response to the information acquired throughout the process. Furthermore, unstructured big health data, such as photographs, videos, and text, may be stored in a variety of forms that are incompatible with traditional big health database storage methods.

2.3 Machine learning

Machine Learning develops efficient automatic predicting systems that generalizes from an observed loop for building or learning. It has a learnable function that usually generates from arbitrary input and output domains [41]. Examples of machine learning are pattern recognition. Pattern recognition in big health data, big health data source rows, big health data content format Pattern extraction Classification Feature extraction segmentation learning via Uniform Formal Learning Model Machine learning VC-Dimension the Runtime of learning Visualization [44].

Automates the process of creating or learning by generalizing from an observable loop. It has a learnable function that normally creates from arbitrary input and output domains [43, 44]. Examples of machine learning are pattern recognition, pattern detection in huge big health data, big health data Source Rows big health data In-content citation Identifying and analyzing patterns Classification Extraction of features Segmentation Learning thru Uniform Model of formal education Machine learning VC-Dimension. The Runtime of learning Visualization system (PRS) and voice recognition systems, which turn unstructured and unknown sequences of information into a language structure, generally in the well-structured format of word strings. The fundamental issues of Machines Learning are acoustic feature sequences occurring as inputs or as the creation of sound waves, which impact the predictive outputs in nominal situations, excluding (unexpected) value for labelling (word or phrase) sequences. The purpose of a learning system is to foresee a fresh output sequence from the novel input order [42]. This prediction procedure, termed recognition, and in most instances referred to as B Classification, after the chronological slice boundaries of the output labels are assumed and properly accomplished. The recognition and Phonetic classification are unlike assignments; the prior is concerned through the form with boundaries given in cooperation with testing and training big health data, whereas the morphology (that is related to phonetic classification) of alphabets does not require any boundary of alphabets and is thus more difficult. As with classification, recognition is a standard machine learning challenge, with the exception of a variable input storage measurement due to big health dataset length variability. Forecast requires the nominal condition to fulfill extra restrictions with various output to manage and grasp a better form of machine learning; Depending on a challenge, continually rising broadcast and new tools are necessary. In the field of artificial intelligence, principles like pattern recognition and computational learning are fundamental building blocks for machine learning algorithms that take use of massive big health data. Machine learning deals with studying methods that may be performed to create correct predictions for following aspects on the basis of the pre-training stage. Artificial neural networks (ANN), a well-known type of learning technique, are primarily predicated on statistical usage to estimate values based on huge samples of inputs. Because it uses numeric values that may be changed as the user gains more expertise, ANN allows for inputs to be used in the learning process. Conversely, ANN is characterized as a system inspired by the human brain to execute big health data that may be utilized to elect a complicated relationship among Inputs/Outputs for processing procedures. An effective ANN model may predict output features as a collection of previously unseen inputs from previously learned features. However, some researches have encountered the limitations of ANN algorithms, and therefore their modified versions were applied **x** and effort on to predict correct features. In the age of big health data, generic models for machine learning employ this foundational idea, but to construct a framework for large-scale predictions, they need the addition of particular tools tailored to massive big health data. ML and big health data mining procedures have strong linkages with mathematical optimization to develop sophisticated models, where programming and creating explicit rule-based methods were previously deemed unfeasible. It is possible to use supervised or unsupervised ML algorithms. In the realm of supervised learning, one of the most common approaches is the ANN. ML provides a new approach of extracting values from diverse big health data sources of big health data based on a big health data-driven operation on a vast machine scale that does not need human engagement. As a result, ML is capable of dealing with the enormous range of factors and the sheer volume of big health data. Big health data may be scaled up using ML while still applying the findings to higher-quality insights, even if typical ML algorithms thrive on expanding big health datasets. The following Table 1 **includes** the core essential principles and techniques to learning big health data, as well as the key explanation of ML, which may lead to interface. These strategies are ideally suited for massive volumes of big health data and may impact big health data implementation Figs. 1, 2 and 3.

Derivative work these letters cite several articles in the summarize in tables and will be plotted based on the prework and post work with influencer. This usually means either field investigation or related recent work inspired by many of the chart's articles. Selecting a derivative will highlight all specified coordinate files it refers to, and selecting a coordinate file will highlight all derivatives it refers to previous job. These are the most frequently cited articles in illustrative articles. This usually means that they are important and original works in the field, and it may be a good idea to learn more about them Table 2.

2.4 Face recognition with disguise

Face recognition was accomplished via the use of vector projection classification (VPC). The AR big health database analyzed the system. Sunglasses and scarves are often used to conceal facial characteristics. In images of sunglasses, the model achieved 62.67 percent accuracy. However, when the images were broken into four parts, the accuracy climbed to 70.00 percent. The accuracy of the scarf images was 6.67 percent, and it rose to 83.33 percent with four partitions. In images of sunglasses or scarves, the accuracy of the KSR (LBP+HK) and KCR-'2 (LBP+HK) approaches was 100%. As a result, the model's accuracy was enhanced, although it was tested on twelve images from AR big health databases. The accuracy of sunglasses images in the SBRC model was 96.00 percent. The model was evaluated using AR big health datasets. Six images were utilized for training and two

Table 1 State-of-the-art to cutting-edge: advancing big health data research

The key research titles	Author	Year	Citations	Graph references
Towards a big health data analytics platform with Hadoop/mapreduce framework using simulated patient big health data of a hospital system	[9]	2016	1	9
Survey on the challenges and issues on big health data analytics		2020	1	8
Interactive big health data analytics platform for healthcare and clinical services	[11]	2018		8
Operational efficiencies and simulated performance of big big health data analytics platform over billions of patient records of a hospital system	[10]	2017	3	7
Protagonist of big health data and predictive analytics using big health data analytics	[45]	2018	2	7
Simulations of Hadoop/mapreduce-based platform to support its usability of big health data analytics in healthcare	[12]	2018	0	7
A survey on big health data analytics: challenges, open research issues and tools	[22]	2016	149	7
Explore the potential impact of big health data challenges, open research issues and various tools associated	[25]	2017	0	6
A survey on big health data analytics: challenges	[5]	2020	7	6
The evolution of cloud computing and its contribution with big health data analytics	[31]	2019	2	6

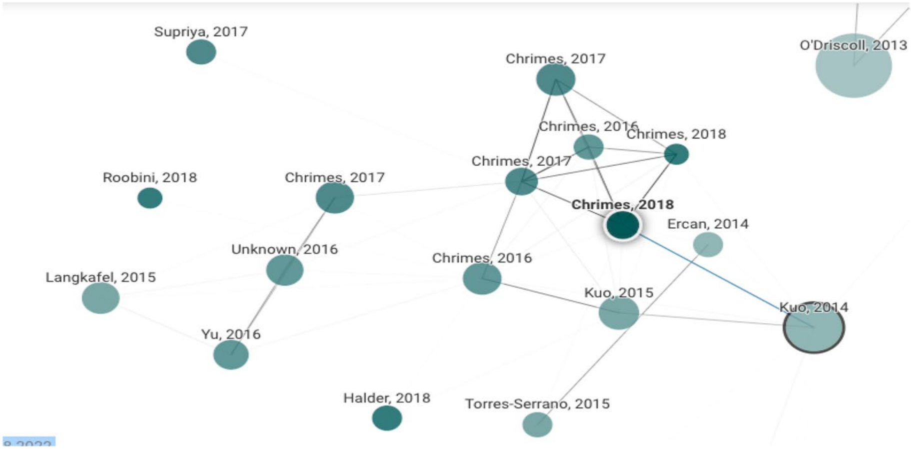

Fig. 1 Investigating a subject in big health data from paper connected (Keyword Big Health March 2022)

images were used just for testing. Although the scarf picture received an 84.00 percent, it was evaluated in two images.

3 Big health data technologies for health and impact

Generally, big health data are significantly large in an unstructured big health data format and cannot be stored in a single machine. As a result, characteristics of handling and processing big health data require special tools and techniques. In particular, state-of-the-art technologies, like Hadoop,

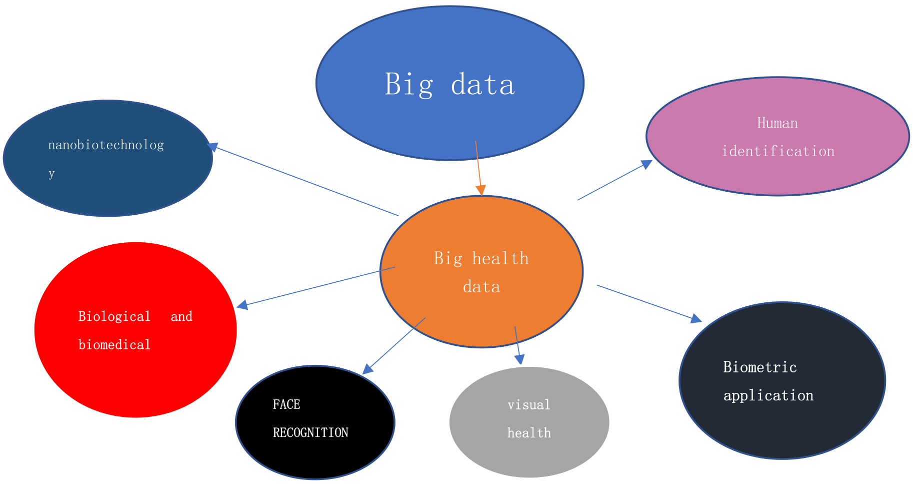

Fig. 2 The taxonomy of implantation big health data in various filed

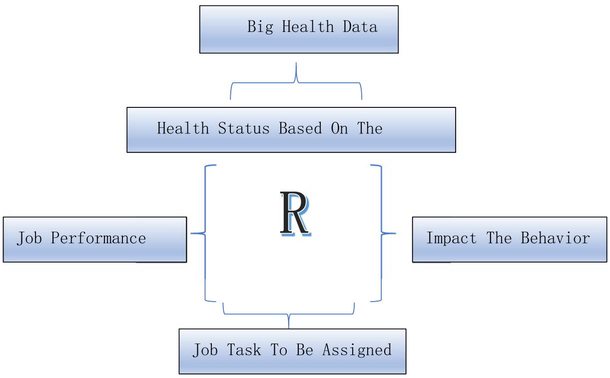

Fig. 3 The application of the big health data in various files matching the needed data into job performance

3.1 Applications of image pattern recognition for big health

Big health data This section presents the relevant application of health pattern clusters for big health data, including biometrics, multimedia, and biomedical/biology research areas, as well as least ensembles with mostly appropriate pattern recognition by merging machine-learning techniques and theoretical achievements.

3.2 Application of multimedia in big health data

Big health data are precisely enormous big health datasets with multimedia, such as images, audios, and videos. Big health datasets are available in and can be captured from specific tools. Multimedia big health data are predominantly highly dimensional, which leads to extra effort to manage with appropriate meaning. In this part, we highlight relevant studies dealing with particular aspects of multimedia in big health data. Feature extraction, visualization, dimensionality reduction, and clustering are examples of intentional approaches dealing with Content-Based and Image Retrieval (CBIR) structures relying on vital reply deliberating on two activities based on standard learning, namely, planned and greedy. In the earlier case study, the greedy method exceeds an optimum by maximizing relevant features for a single query at every step. The planned techniques representing the well-known informative. Features are called back via a certain number of repetitions, with the most important case only achievable at the later stage. OPF evaluates the results on user effectiveness and efficiency. In a status technique of simple features relied on contextual information. The effort revealed on the CBIR method could facilitate indexing and labeling in the enormous features that are set into describing duplicate digital and historical health images in such a case. features are the most focused material issues in the CBIR methods. In most cases, feature vectors are results of matching and color attributes from a High-Dimensional feature space. In labeling/indexing approaches for a feature collection were identified as the main key issues for dealing with extraordinary size, dimensions, and big health data sets (having over While googol = 10^100 and =10^googol mean while googolplex of yottabyte of features witch far then any single machine able to represented it). These techniques were fast, and approximated extractions were attainable. In feature assembly exploration was conducted aimed at carrying out results by different ways to achieve origin features through four aspects, namely, a mutual content and representation, interaction, visualization and summarization. A well summarization and illustration phases

Table 2 Selecting a prior-post referencing it, and selecting a graph paper will highlight all referenced prior work

Title	Author	Year	Citations	Graph citations
Big health data: the next frontier for innovation, competition, and productivity	[27]	2011	4850	10
Computational solutions to large-scale big health data management and analysis	[34]	2010	585	8
Cloud computing: a new business paradigm for biomedical information sharing	[32, 33]	2010	359	8
Business intelligence and analytics: from big health data to big impact	[8]	2012	4219	7
Bioinformatics clouds for big health data manipulation	[13]	2012	151	7
Cost-effective cloud computing: a case study using the comparative genomics tool, roundup	[24]	2010	50	7
A view of cloud computing	[3]	2010	9392	7
An overview of the hadoop/mapreduce/hbase framework and its current applications in bioinformatics	[38]	2010	486	7
Big health data in science and healthcare: a review of recent literature and perspectives. contribution of the IMIA social media working group	[17]	2014	108	7
Opportunities and challenges of cloud computing to improve health care services	[26]	2011	376	7

were established on a Kernel Conversion to solve the issue of dimensionality reduction. For B Histological Images^, aggregation n Expert-Labeled TA form, a set of attributes encompassing both visual and textual big health data, was used in the classification stage to make use of the extraction. Clustering and analysis approaches employing the same set of histology images were also applied in another work [35]. This research coupled bag-of-features reports with high-level dimension in order to come up with a feature collection set that was acceptable for the study's objectives and objectives. Developing a common framework for analyses with high performance for features to ensure the appropriate description and conduits, as well as varied groups for image-processing analysis jobs, was made feasible (such as annotation, feature extraction, and classification). This method is unable to detect duplicate features across multiple applications, despite the fact that it has been used to lease search space functions for a large quantity of big health data using standard subgraph mining techniques. In addition to develop and confirming the parallel graph-pruning strategy, this researcher employed the methodology to show a chart-based visual. Prerecorded qualities are expressed in this case by the employment of a graph with a particular quadruple-tree structure. An arrangement of normal sub-diagrams is obtained and utilized as information components by the SVM classifier, which use finite state machine algorithms to accomplish this task. There are several examples of mining analogies, and they are often provided in [.Approaches]. 3D pyramids may be used to build a challenge that demands participants to recognize photographs by joining images together using dividers.

In order to keep track of how closely related traits are, a graph-coordinating approach was proposed. The displaying procedure achieves the content of an image and was handled in [4] by the addition of big health data to the spatial design of the image via its component descriptors. In light of the Fisher Vector-Coding technique [21], two solutions were offered, which employed declining points per difference classes while improving their continuous reparability. Thus, arrangement precision was employed in this approach to highlight vectors. Calculations begin per patch of 25 * 25 pixels after 128-Dimensional scale-invariant feature transform descriptors [4] were validated. In general, the approach was demonstrated by applying the PASCAL-VOC, consisting different big health data versions of the 2007, 2008, and 2009 big health datasets, encompassing attributes per 20 sorts of items. For certain big health data, video big health data seems to be more damaging than the rest. A real record set is shown in three-dimensional form (in two-dimensional space with time added) or stretches out to four-dimensional space (in three-dimensional space with an additional factor of time added). As many as three (or more) different color modules may be used in any one instance in this multi-dimensional space. As a result, video recordings carry huge volumes of information in its higher dimensions, and knowing processes for categorizing and retrieving from these big health datasets was vital. In, they introduced a way to construct a mutual demonstration in a low-representation Boolean space for information that depends on numerous manifolds, nicknamed the Laplacian eigen map approach. This approach was employed to uncover transitory and unique links among video frames. A few videos big health datasets were studied, in which every edge was considered a single edge with a high-dimensional space, such as 4880, 3600, 16,384, and 19,200, and more than 100 examples for everyone. This technique was additionally connected to four biomedical big health datasets managed to accomplish from excessive endurance of various sicknesses and healthy individuals, both from differing sources electroencephalogram (EEG), voice recording, and phonocardiography, primarily used to highlight the space dimensionalities. In addition, a strategy was supplied for brief video content centered on misusing visual components deleted from the streamlined video devoid of decoding.

Various approaches blast the search for visual content in limitless big health data applications, such as video dispersion in social networking and intelligence reconnaissance. The research in benefits from shape models (SMs) to show a fresh outside item within video in light of their projection compared with similar models. High-arrange SMs (up to 25 eigen modes) were provided to exchange with essentially similar object classes and the regular differences within them, with each shape believed to be a unique point in complex geometries (starting from 28,000 components). Most parallel indexes were achieved by relating the first interactive media objects into less complex representations, which were then sought by closeness by utilizing a suitable separation capacity. As a case, mixed media objects were represented as collection of set where all contains only numbers, with a separation that was elaborate via utilizing set operations. In this proposed demonstration where is allowed queries during central memory notwithstanding not the case for huge big health databases (the searcher showed their outcomes with 100,000 features). Another similar research addresses the same content where had investigational in a correlation of the proficiency and adequacy of unlike elements was organized. The preliminary examination distinguishes between the small-scale big health data set and the elements of the large big health database containing not less than 23*104 features.

3.3 Biometric application

Since the biometrics system depends on face, eye, and fingerprint recognition, researchers have had to wrestle with the concept of working with large health big health data volumes. The size and features of the set also play a significant role in major productions. A growing number of efforts have been made to simplify biometric traits and make classification systems more efficient. A multi-objective wrapper is implemented in the face recognition system to determine the most relevant set of attributes. Research regularly incorporates Dimensionality Reduction approaches, such as the studies which deals with face recognition via a synthesis of 2D and 3D information. This 3-dimensional feature vector was constructed by combining the geodesic expanses at distinct points on the appearance, such as the noise features. However, geodesic distances from varied places of appearance, such as the slope of the noise, are connected to form a High-Dimensional Feature Vector. The results were regenerated using SVM to classify the attributes. A demonstration of a face merged in images of features was obtained, which investigated the stability and smoothness of the facial image and simultaneously dealt with the dimensionality issue. In [6] each facial feature was specified by a recognition technique coupled with a different function, including functional spaces was defined. New strategies were built for the face identification methodology based on boosting cascade classifiers by performing a variety of images. The image in [6] deals with face verification in a video sequence captured by a smartphone. Although fingerprint recognition is a vital field, automated fingerprint identification approaches encapsulate the direction of research throughout the preceding four decades. However, substantial work is still necessary for current areas with complicated obstacles, such as reducing noise from image characteristics that require uniqueness, such as high intraclass variation numbers and/or wrongly acquired big health data (incorrect fingerprint detection). There could be billions of records in these systems, hence categorization and strategy creation for such a job frequently needs working swiftly, human identification systems have also relied on iris and fingerprint patterns.

3.4 Biological and biomedical applications big health data

Biomedical and biological procedures cover numerous classifications and areas within the same field, concerning a wide range of science areas, including molecular, biochemistry, biotechnology, biophysics, cell biology, nano-biotechnology, virology, biostatistics, microbiology, biological engineering, genetics, and bioinformatics. Different large-scale health data collection methodologies are commonly employed to establish the functioning of these varied application domains. The large majority of them produce considerable and distinct volumes of heterogeneous big health datasets to be evaluated in order to extract useful (quantitative or qualitative) information. Few research has centered on these subfields by analyzing obstacles linked with microarray processing and gene expression. To display them, the SVM-recursive and feature elimination SVMRFE is done on the multi-variety gene election and selection of limit biology and enormous health datasets with key genes for investigation within a microarray set. The B-Sparse-S technique, which has the same concept as the BSVMRFE routine and traverses' numerous stabs of gene elimination, is maintained by separation and a well stabilized selection. The algorithms are evaluated by applying simulated large health data, containing three physical big health datasets with 4434 genes, ranging from 3051 to 2000 gen features for each test case. The utilization of neural network models developed on SOMs for finding correlations between metabolites and gene expression is given. In such scenario, single vision is crucial for detecting the boundary as well as spotting synchronization discrepancies in metabolites and mRNA. The sequence of information and roughly 8000 mRNA genes are covered by the vast health database based on genes. Classification genes that were connected morphologically to the confrontation of various diseases in a single plant were the subject of the study in (Schadt,2020) which offered several clustering approaches to associate genes and their expression with patterns occurring within microarrays. The examination of different pattern recognition algorithms is an outstanding example of a large-scale microarray health data investigation. Magnetic resonance imaging (MRI), microscopy, and computed tomography all come under the category of image processing technologies. They produce large numbers of health datasets, many of which are polluted by various sorts of noise. The diagnostic approaches in both 2D and 3D features are important for dimension resolution. A single system can't contain the huge data of unstructured big health data that are regularly generated. As a consequence, components of organizing and evaluating massive amounts of health data necessitate specific tools and methodologies. Modern technologies, such as Hadoop, in particular.

4 Applications of visual health pattern

For massive big health data, this part provides the applicable application of health pattern clusters for large big health data, covering biometrics, multimedia, and biomedical/biology research domains, as well as least ensembles with mainly acceptable pattern identification by integrating machine-learning methods and theoretical accomplishments.

4.1 Use of multimedia in large big health data systems

The term "big health data" refers to a collection of information on an individual's health that may include a variety of different types of images. Large health datasets may be collected using a variety of methods. Because multimedia large health data tend to be multi-dimensional, it requires more time and effort to understand them appropriately. In this area, we highlight important studies dealing with different features of multimedia in large health data. Biomedical and biological procedures cover numerous classifications and areas within the same field, concerning a wide range of science areas, including molecular, biochemistry, biotechnology, biophysics, cell biology, nano-biotechnology, virology, biostatistics, microbiology, biological engineering, genetics, and bioinformatics. These different application disciplines generally construct their functioning by using unique large-scale health data collection approaches. The large majority of them produce enormous quantities of various heterogeneous big health datasets that must be examined in order to extract meaningful (quantitative or qualitative) information. The problems of microarray processing and gene expression have only been briefly examined in a few research. SVM-recursive and feature removal were used to demonstrate SVMRFE is a technique that uses a microarray set to pick significant genes from a large number of candidates using a multi-variety approach. It is possible to retain the B-Sparse-S technique, which uses numerous stabs of gene removal and is conceptually similar to the BSVMRFE routine, by performing separation and a well-stabilized selection. For each of the three physical big health datasets, the data are evaluated on a collection of 4434 genes, spanning 3051 to 2000 gen features. The utilization of neural network models developed on SOMs for finding correlations between metabolites and gene expression is given. In such scenario, a single image is incredibly vital for figuring out where the boundary is and observing how metabolites and mRNA are different at the same time. The application of the vast health database published on genes comprises the sequence of information and contains roughly 8000 mRNA genes. As part of the project, several clustering methods for experience genes and their expression with patterns emerging within microarrays were provided in order to link morphologically-associated categorization genes to the encounter with diverse diseases in a single plant. The development of diverse pattern recognition algorithms is a noteworthy example of a large-scale microarray health data analysis. MRI, microscope, and divide tomography are all image processing techniques. They produce huge amounts of massive health datasets, which are frequently polluted by multiple noise sources. Diagnostic processes in both 2D and 3D aspects are identical. Massive data of unstructured large health data can't be kept on a single system because of their sheer size. As a consequence, components of organizing and evaluating massive amounts of health data necessitate specific tools and methodologies, particularly cutting-edge systems like Hadoop.

A decent summary and illustration phases were established on a kernel conversion to solve the challenge of dimensionality reduction. B-Histological Images employing form to categories a set of features, including visual and textual content, using Expert-Labeled Text in [46]. In Armbrust, the same set of histology images was utilized for analysis and clustering methods once again. This research merged bag-of-feature reports with high-level dimension in the process of attaining an optimal feature collection set. To ensure appropriate descriptions and conduits, a number of analytical frameworks with excellent performance features were constructed in (Such as annotation, feature extraction, and classification) [4]. For a big health data collection, common sub-graph mining [19] was applied, however it was impossible to detect duplicate features across apps due of its tiny feature size. As reported in [46] , the researcher employed the parallel graph-pruning approach to show a framework for chart-based images [19]. These results were then corroborated. A graph with a special quadruple-tree structure is used to express prerecorded characteristics in this situation. SVM classifiers may make use of finite state machine approaches to acquire information about standard sub diagrams. Examples of mining constant tantamount were originally given in [19], while examples of mining regular comparable were provided in [46]. In [21], approaches for mixing visual aspects of images (e.g., shape, color, and textures) with spatial links among distinct portions were established, which were done from the dividers of 3D pyramids to provide an identification challenge. In order to keep track of how similar particular qualities are, a graph-coordinating system was designed. An image's content was represented in [46] by adding spatial design and health data via component descriptors to its portrayal. In light of the Fisher Vector-Coding technique, two ways were put up, both of which utilized lowering points per difference class while concurrently boosting their reparability [21]. As a consequence, this approach for feature vectors needs arrangement precision. Accepted by 128-Dimensional scale-invariant feature transform descriptors [6], calculation was initiated per patch of 25 * 25 pixels. PASCAL-VOC was used to demonstrate the effectiveness of the method by combining large health datasets from 2007 to 2009, each of which included information on 20 different types of entities.

Video big health data is most likely a more severe version of media large health data. A record set must be presented in a three-dimensional (3D space with an additional time factor) or four-dimensional (3D space with an additional time factor) format to be regarded valid. There may be as many as three (or more) distinct color modules in any one occurrence in this dimension. Because of the sheer volume of data included in video recordings, it was imperative that methods for accurately identifying and retrieving data from these massive health datasets be well understood. I suggested a way to produce a mutual demonstration in a low-representation B-dimensional space for information that depends on many manifolds, appealing to the Laplacian eigen map approach. Transient and unique connections between video frames were identified utilizing this strategy. Large health datasets, such as 4880, 3600, 16,384 and 19,200 with terms bigger than 100 cases each, were examined in which every edge was viewed as a single edge in a high-dimensional domain It was also applied to highlight the spatial dimensionalities of four physiologically relevant datasets, including electroencephalograms (EEGs), voice recordings, and phonocardiograms, which were obtained from patients with varied diseases and in good health. A technique was presented for brief video content focusing on misusing visual components omitted from the streamlined video devoid of decoding. When employing unlimited large health data applications like video dispersion in networking or intelligence reconnaissance systems, numerous ways explode visual content evaluation. The work in [19] makes use of shape models (SMs) to show a fresh outside item within video in light of their projection compared with relevant models. As a consequence, high-dimensional SMs (up to 25 eigen modes) were supplied for interchange with object classes and the regular differences within them, with each shape signifying a unique point of high dimensional complexity (starting at 28,000 components) (beginning at 28,000 components). Most parallel indexes were generated by connecting the original interactive media elements into less sophisticated representations, which were then examined for proximity by applying a suitable separation capacity. Set operations were employed to build an extensive differentiation between mixed-media artifacts and other collections of sets that include purely numbers. within This gave evidence where authorized searches while in central memory, despite not being the case for enormous, massive health databases (the researcher presented their findings with 100,000 features) (the researcher demonstrated their outcomes with 100,000 features) (the researcher showed their outcomes with 100,000 features) [46] is similar research that examines the same subject content. A connection of the proficiency and adequacy of unlike components was organized. For the time being, the early findings distinguish between the smaller, more localized collection of large health data and the massive global database, which has no less than 23*104 features. Video big health data is most likely a more severe version of media large health data. 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4.2 Biometric application

Researchers have had to contend with the issue of working with huge big health data sets since the biometrics system is built on the collection of biometric qualities such as face recognition, iris recognition, and fingerprint identification. This is why the idea of space size and qualities also plays a large role in massive installations. Classification algorithms that successfully reduce the dimensionality of biometric traits have been the subject of several efforts. The face recognition system uses a multi-objective wrapper to choose the best optimal set of characteristics for processing. Dimensionality reduction methods, such as the studies, are extensively utilized in research. The implementation of facial recognition by combining 2D and 3D data. However, a high-dimensional feature vector was created by connecting the geodesic extent from various parts of the appearance, such as the tip of the noise. However, geodesic distances from varied places of appearance, such as the slope of the noise, are connected to form a High-Dimensional Feature Vector (HDFV). The results were regenerated using SVM for categorizing the properties. A demonstration of face merged in images was accessible, which respected the stability and smoothness of the facial image and simultaneously dealt with the dimensionality issue. In a recognition process associated to unique functions, including functional zones, was established for each of the facial traits. New strategies were built for the face identification methodology based on boosting cascade classifiers by performing a variety of images. Face verification is the subject of this image, which was captured on a cellphone video. Automated Fingerprint Identification Systems (AFIS) have assumed the position of manual fingerprint identification in research throughout the preceding four decades, despite its relevance. While the current field has several challenges, such as removing noise from image attributes, ensuring uniqueness by accounting for huge intraclass variation numbers, and/or dealing with incorrectly collected vast amounts of health data, much work remains to be done (incorrect detection of fingerprint). Furthermore, the enormous health data set in these systems may search billions of records, thus speed is normally a demand during classification and development processes for such a work. Human identification has also depended on iris and fingerprint patterns. Biological and medical applications it is possible to classify big health data in biomedical and biological procedures into numerous subfields within the same field, including molecular and biochemical, as well as biological and biophysical fields like cell biology and nanobiotechnology. Also included are biostatistics and microbiology fields as well as genetics and bioinformatics fields. Different large health data collection strategies are often employed to develop the capability of these distinct application disciplines. Large, diverse health datasets are generated and processed in order to get actionable information from these sources. Only a few studies have investigated the problems of microarray processing and gene expression in these specialized subfields. To illustrate them, the SVM-recursive and feature elimination SVMRFE is done on the multi-variety gene election and selection of limit biology huge health datasets with significant genes for investigation inside a microarray collection. With the B-Sparse-S procedure, which uses numerous stabs at gene removal and is based on the BSVMRFE routine, new concepts may be explored in the future via separation and well-stabilized selection. The approaches are evaluated by applying fake large health data, containing three physical big health datasets through 4434 genes and extending from 3051 to 2000 gen features for each test case. SOM-based neural network models are provided for the purpose of discovering metabolite-gene expression correlations. In this case, a single viewing is needed for defining the boundary and comparing differences in metabolite and mRNA synchrony. The employment of appearance huge health database relay on gene covers the sequence of information and comprises roughly 8000 mRNA genes. In the attempt concerned with categorization genes that were connected morphologically with the confronting of various illnesses in a single plant by using numerous clustering techniques to evaluate genes and their expression with patterns occurring inside microarrays. The discovery of numerous pattern recognition systems using microarrays and large-scale health data sets is one notable example. "Magnetic

Resonance Imaging" (MRI), microscopy, and divide tomography are only a few of the image-processing methods. They create vast volumes of big health datasets constantly affected by numerous noise factors. Diagnosis procedures in two-dimensional and three-dimensional features are required for dimension resolution and model reconstruction. Potts models and Gaussian Markov randomness have been used to provide novel methods for categorizing and using multispectral data in context, the favorable structure of MRI analysis was stressed. In the building of a novel structure dealing with classification, averaging, and alignment of dimensions produced as an electronic tomography source was presented, discusses image processing techniques that make advantage of dermatological traits. Used similarity to choose important attributes. employed a machine-learning approach to categorize melanocytic lesions as benign or malignant, and it was extended in dermato-scope features. EEG signals and massive big health data sets have both presented unique challenges when it comes to identifying meaningful descriptions. In other studies, the use of sound and speech, as established by natural reflection by laryngoscopy, has been extended to the diagnosis of sickness. In this case, speech identification and analysis are the major issues in acoustic analysis in an independent corresponding strategy to complete diagnosis. An estimate utilizing various unsupervised and supervised learning techniques for dimensionality reduction performances was provided. This example leads to displaying signals for speech recognition using a classifier. The Messy Voice large health database does not give signals for speech recognition, and big health databases like the Ear and Eye big health databases require additional resources. Speech recognition considers a feature vector of greater dimension level, which is collected via reproducing original features. Correspondingly, the work in created a feature representation size based on the HMM for conversion, allowing optimum discriminating between sick and normal features [46].

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However, geodesic distances from varied places of appearance, such as the slope of the noise, are connected to form a High-Dimensional Feature Vector (HDFV). The results were regenerated using SVM for categorizing the properties. A demonstration of face merging in images was offered, which considered the stability and smoothness of the facial image and simultaneously dealt with the dimensionality issue. In recognition process associated to unique functions, including functional zones, was established for each of the facial traits. New strategies were built for the face identification methodology based on boosting cascade classifiers by performing a variety of images. The image deals with face verification in a video sequence captured. Automated Fingerprint Identification Systems (AFIS) have assumed the position of manual fingerprint identification in research throughout the preceding four decades, despite its relevance. While the current field has several challenges, such as removing noise from image attributes, ensuring uniqueness by accounting for huge intraclass variation numbers, and/or dealing with incorrectly collected vast amounts of health data, much work remains to be done (incorrect detection of fingerprint). Furthermore, the enormous health data set in these systems may search billions of records, thus speed is often essential during categorization and development methods for such a work. Human identification has also depended on iris and fingerprint patterns. Biological and medical applications It is possible to classify big health data in biomedical and biological procedures into numerous subfields within the same field, including molecular and biochemical, as well as biological and biophysical fields like cell biology and nano-biotechnology. Also included are biostatistics and microbiology fields as well as genetics and bioinformatics fields. 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In order to categorize melanocytic lesions as benign or malignant, used a machine-learning approach and included other dermato-scopic parameters. Different techniques of tackling the difficulty of acquiring adequate descriptors in EEG signals and high dimensionality in massive, big health data sets were offered. In other studies, the use of sound and speech, as established by natural reflection by laryngoscopy, has been extended to the diagnosis of sickness. In this case, speech identification and analysis are the major issues in acoustic analysis in an independent corresponding strategy to complete diagnosis. In an estimate utilizing various unsupervised and supervised learning techniques for dimensionality reduction performances was provided. This example leads to the display of signals for speech recognition by a classifier. 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4.3 Impact of health on job performance

A growing number of individuals struggling with the unhealth condition (physical or mentally) of the employees affecting both on job performance and organizational performance by shows the low quality job performance and the low productivity [20]. There is direct evidence showing that majority of the organization costs linked with the employees' health conditions are in the forms of impaired performance. According to a study has been conducted by Bank one in the U.S it shows 63% of health-related costs are connected with employees being at work but not at full vigor, compared to 24% involved with direct medical and pharmaceutical spending [16]. As in the daily life, some of the employees will continues working while\B impaired by physical ailments: such as headaches, catch the cold, pain and other common sickness; in the psychological side, the depression, anxiety and psychological strain may also influence work ability and motivation to perform [47].

4.3.1 Mental health conditions at work

The DSM-5(Diagnostic and Statistical Manual of Mental Disorders fifth Edition) has listed 157 different conditions. Individuals may be diagnosed with one or more illnesses as a result of medical health specialists observing and assessing their symptoms. It has been discovered that mental health issues have a negative impact on organizational performance, for example, the research on individuals, with anxiety and depression has direct impact on concentrations, decision-making process and risk-taking behavior also get affected this can be determined for the organizational performance [18]. Moreover, the job performance has direct impact when the individuals employees struggling with ADHD (Attention Deficit Hyperactivity Disorder) while the job-tasks is under the time pressures [20].

4.3.2 Physical health conditions at work

Somatic complaints/symptoms, high blood pressure and obesity are the three categories that reflects aspect of physical health that commonly cited as the reasons for health-related to work impairment; Moreover, the high blood pressure and obesity represent two of the most important current work challenges to public health worldwide [15].

Somatic complaints/symptoms has potential possibility to reduce the employees tasks performing by diverting the work memory and information processing capacities away from the work tasks meanwhile causing the somatic issues such as pain and discomfort, it also interfering with an individuals' cognitive resources and ability to perform, it also occur the decline of ability and motivation to perform in the job tasks by reducing the individuals" well-being [1].

High blood pressure is one of the reasons to cause the employees to reduce the work performance in the tasks by it shows a frame of consciousness that may affect task or context performance. High blood pressure is also a sign of inefficient cardiovascular system use, which is likely to lead to its deterioration over time. The higher blood pressure is also associated with reducing the job performance [7].

Obesity can cause the massive demanding in the physically job performance. however, the majority of the job tasks does not high requirement in the physical conditions such as officers, programmers, tec, it might has limited effects on these jobs [23].

4.3.3 Employees job performance and organizational performance

The employee performance is very important for the organization to be succeed in the competitive market, it's one of the most important indicators for the organization to achieve the goals. Companies nowadays have been forced to act professional in the market, so it is very important to have the employees be able to act and complete the tasks and to push the companies performing well and gain the profit in the market [1]. According to Wall et al., [40] mentioned in his study that the employee performance has great impact on the organization performance.

5 Methodology and data analysis

5.1 Methodology

The study used the quantitative research design to investigate the relationship among the big data on health condition of the employees and the employees' job performance. The target sample population of this study was the employees who is aged 55 years old and above working in the SOEs of mainland of China. As sample for experiment of size was 327 stuffs with their medical recodes, based on quarry responses will collected for mainland of China. This research used SPSS for data analysis.

The Fig. 4 is the demographic profile of the respondents in terms of gender, current/previous occupational positions, and health conditions? In terms of gender, 66.36% of respondents are females, 33.64 are males, the majority of respondents are healthy (66.97%), 30.58% have common geriatric disease, and the remaining 2.45% have occupational disease; in terms of current/past job positions, 20% are accountants, followed by sales and management level.

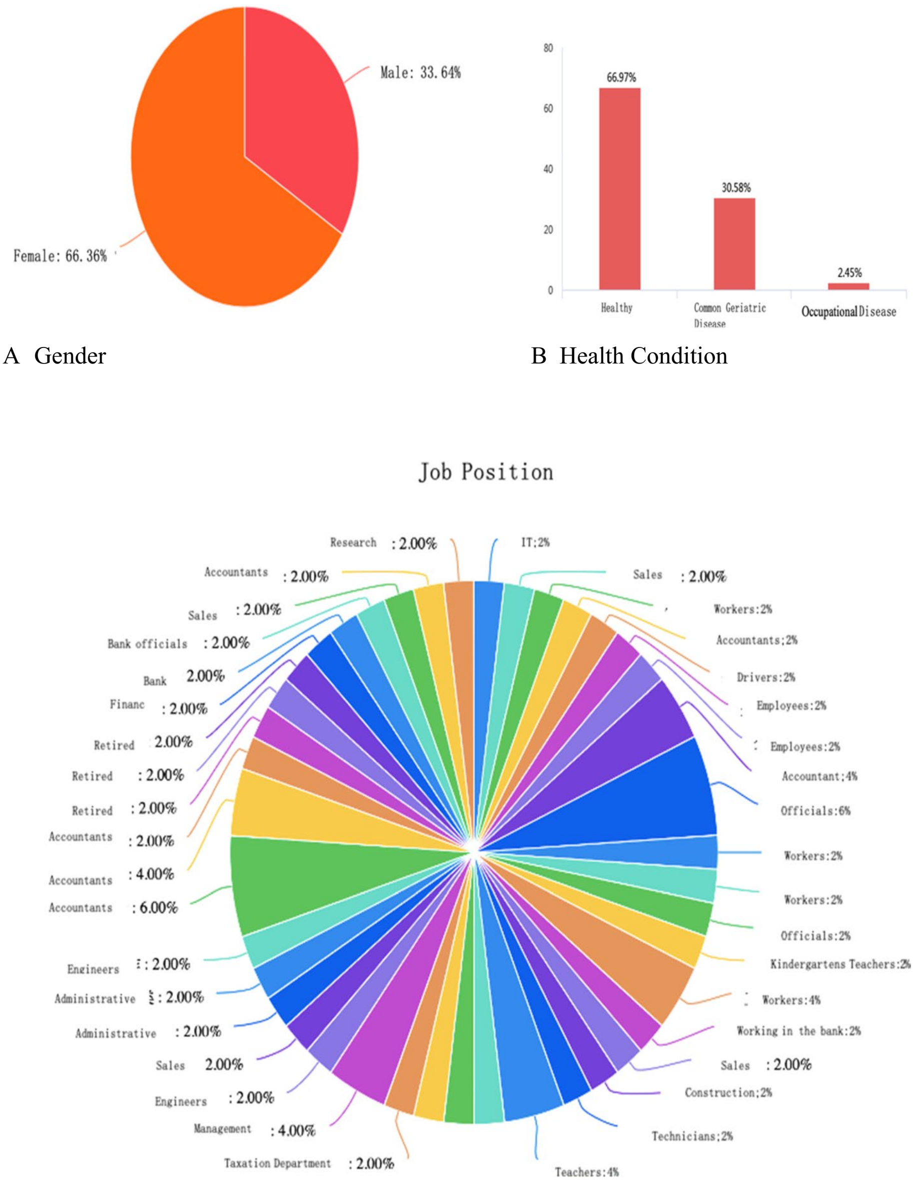
5.2 Data analysis and discussion

The aims of this study were to examine the impact of big data of elderly employees' health condition on job performance. Measuring the model, the large number of parameters need to tested. In order to avoid the problems among these, the research adopt the structure model. The analysis based on the questions related to the gender, current job positions, the health conditions and suitable job tasks the candidates think they are suitable for. The Chi-Square (cross-table) analysis will be conducted in this research for cross analysis of the questions based on the gender, to examine the relationship among the health condition, current job position and the suitable jobs.

Re-scaling the management health system was successful because it fit with the company's culture.

Resizing the prototype experiment into Size.={327 patient enroll as subset of big health data }

We defining the parameters by the clusters ,{job ,job performance , health condition }



A Gender

B Health Condition

C The Current/Past Job Positions

Fig. 4 The demographic profile of the respondents (N=327)

We defining assigning new task based on the clusters ,{job, job performance, health condition } by the function RAS={}

While the

k=1 Koja = size do {N = total number

1 After calculating the expected value, we will apply the following formula
2 to calculate the value of the Chi-Square test of Independence:
3 First, we will compute the anticipated value of the , and then we will use the following formula to get the Chi-Square }

end while

the shape of your graph is. It's conceivable that its tails will be stocky. It's conceivable it's had long, slender tails. You just do not comprehend. The area in the tails of the t-distribution reduces as the number of degrees of freedom (df) rises; the area in the centre of the distribution increases as the number of degrees of freedom (df) decreases, The t-distribution will approximate a normal distribution when the value of df approaches infinity. When this happens, you may be sure about your big health data's standard deviation (which is 1 on a normal distribution).

Let we define the function f(Q) where is the function detriment the plot of each question Q1...QN

Such as Q is the variable of the question**Let Define:** the aggregate function or the relation function R(V, Y) denoted as:

R(v , y) as|V|length and|y|=5 V(QX,QX2,QX3,QX4,QX5)RY(QN,,,,,QN) contagion the plot of

such as v, yi vector of length | V |= 5 contagion the plot of the function f(Qn).

SP(R(V, Y)): solution plots: is a solution function of HAVING after GROUP/clustered to set criteria to calculate the expected value of the nominal

variables

if SP(R(V,Y))= 0

SP (R(V, Y))As : else SP(R(V,Y)) = Z [4]

length | Z |= m

if SP(R(V,Y))= 0 they were zero cluster witch is impossible case due te big health data enter to returns (0) else return SP(R(V,Y))= Z :

where z is n integer infinite set with length | Z |= m.

m: is the is maximum solutions provided by solution SP(R(V,Y)).

As can be seen from the above table, use chi-square test (cross-over anal- ysis) to study as a set of Q [4–6, 8, 19]. There are 4 differences in the relationship, as can be seen from the above table: different with [4, 5] [5, 6, 19] The sample is A total of 3 items will not show significance (p¿0.05), which means different 4.5 14) How long it's your seniority? The sample showed con- sistency for all 3 items of there is no difference. In addition, [4, 8]. (p¡0.05), which means different significance

4,7 A total of 1 item all show differences. Specific suggestions can be compared with the percentages in parentheses.

As can be seen from the above Table 3, it uses the chi-square test (cross analysis) to study the 4 questions on Your gender: For What is your previous/current job? , How is your health status? , Which of the following types of work do you think is suitable for

Table 3 Chi-square(cross-table) analysis on health conditions based on gender

3. what is/ your job positions?	It	1(3.33)	0(0.00)	1(2.00)	47.222	0.201
	Sales	0(0.00)	1(5.00)	1(2.00)		
	Instrument Engineers	1(3.33)	0(0.00)	1(2.00)		
	Accountant	1(3.33)	0(0.00)	1(2.00)		
	Driver	0(0.00)	1(5.00)	1(2.00)		
	Office Employees	0(0.00)	1(5.00)	1(2.00)		
	Administrative	0(0.00)	1(5.00)	1(2.00)		
	Accountant	2(6.67)	0(0.00)	2(4.00)		
	Officer	2(6.67)	1(5.00)	3(6.00)		
	Worker	0(0.00)	1(5.00)	1(2.00)		
	Worker	1(3.33 was)	0(0.00)	1(2.00)		
	Administrative	1(3.33)	0(0.00)	1(2.00)		
	Pre-Education	1(3.33)	0(0.00)	1(2.00)		
	Worker	0(0.00)	2(10.00)	2(4.00)		
	Bank	1(3.33)	0(0.00)	1(2.00)		
	Sales	0(0.00)	1(5.00)	1(2.00)		
	Construction Engineer	1(3.33)	0(0.00)	1(2.00)		
	Engineer	0(0.00)	1(5.00)	1(2.00)		
	teacher	0(0.00)	2(10.00)	2(4.00)		
	Cashier in the bank	1(3.33)	0(0.00)	1(2.00)		
	Administrative officer	0(0.00)	1(5.00)	1(2.00)		
	officer	1(3.33)	0(0.00)	1(2.00)		
	Officer in the taxation department	1(3.33)	0(0.00)	1(2.00)		
	manager	0(0.00)	2(10.00)	2(4.00)		
	engineer	1(3.33)	0(0.00)	1(2.00)		
	sales	0(0.00)	1(5.00)	1(2.00)		
	officer	0(0.00)	1(5.00)	1(2.00)		

Table 3 (continued)

	Administrative officer	1(3.33)	0(0.00)	1(2.00)		
	engineer	1(3.33)	0(0.00)	1(2.00)		
	cashier	3(10.00)	0(0.00)	3(6.00)		
	cashier	2(6.67)	0(0.00)	2(4.00)		
	Accountant	1(3.33)	0(0.00)	1(2.00)		
	retired	1(3.33)	0(0.00)	1(2.00)		
	Administrative officer	0(0.00)	1(5.00)	1(2.00)		
	retired	1(3.33)	0(0.00)	1(2.00)		
	Fiancé department	1(3.33)	0(0.00)	1(2.00)		
	bank	1(3.33)	0(0.00)	1(2.00)		
	bank	1(3.33)	0(0.00)	1(2.00)		
	sales	0(0.00)	1(5.00)	1(2.00)		
	Sales	1(3.33)	0(0.00)	1(2.00)		
	Academic Research	0(0.00)	1(5.00)	1(2.00)		
Total		30	20	50		
4. Health Condition	Healthy	22(73.33)	9(45.00)	31(62.00)	4.869	0.088
	Common Geriatric Disease	8(26.67)	10(50.00)	18(36.00)		
	Occupational Disease	0(0.00)	1(5.00)	1(2.00)		
Total		30	20	50		
7. The Job Suits You	Academic Research	1(3.33)	5(25.00)	6(12.00)	19.242	0.000**
	Technology	5(16.67)	11(55.00)	16(32.00)		
	Management	14(46.67)	4(20.00)	18(36.00)		
	Administrative Tasks	10(33.33)	0(0.00)	10(20.00)		
Total		30	20	50		

* $p<0.05$ ** $p<0.01$

your personality? There are a total of 3 differences between the relationships, which can be seen from the above Table 3: the gender for questions related to previous/current job and the health status, in total the 2 items did not show significance ($p>0.05$), which means the different between questions related to the gender for questions related to previous/current job and health status was no difference among these questions. In addition, the gender related to the questions for which types of work does candidates think their personality is suitable for? It shows significant ($p<0.05$), which means the different between gender and suitable job tasks shows the differences relationships.

Compare the gender to the questions related to the suitable job tasks shows significant differences (significant at the 0.01 level chi=19.242, $p=0.000<0.01$)

By comparing the percentages, it can be seen that 25.00% of male chose academic research, which was significantly higher than that of female, 3.33%. The proportion of males choosing technical categories (eg: engineers, skilled workers, etc.) was 55.00%, which was significantly higher than that of females (16.67%). The proportion of women who choose management is 46.67%, which is significantly higher than that of men, 20.00%. The proportion of women choosing administrative copywriting is 33.33%, which is significantly higher than that of men who choose 0.00%.

The Fig. 5 above is the cross analysis among the health condition and the whether the respondents have/had face the communication issues among the colleagues at the workplace, in the figure the blue represents the answer"yes" the green represents "no" under the different health conditions which are "Healthy", " Common Geriatric Disease" and "Occupational Disease". From the results can be seen that the elderly employees with Common Geriatric Disease are/were face the communication issues (76.04%), followed by the healthy group which is 75.6%. On the contrary, the group has occupational disease has only 57.14 % of respondents are/were face the communication issues among the colleagues meanwhile it has 42.86% of respondents are/were not face any communication issues which is the highest group by comparing with "Health" and "Common Geriatric Disease".

As the conclusion, compare the questions related the gender to previous/current job and health status, did not show significant difference among these; Compare the questions related to the health conditions and whether they have/had faced the communication issues among the colleagues at workplace, it clearly shows that with different health conditions has impact on the communication issues, the group has less communication issues is the employees has occupational disease. In addition, compare the gender with questions and health conditions with communication issues related to suitable job tasks, showed a significant difference Fig. 6.;

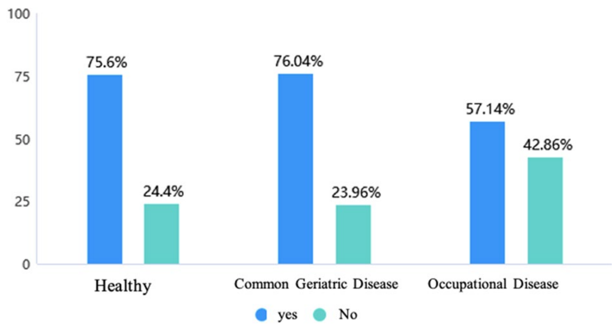


Fig. 5 The comprising of health condition and communication issues at the workplace

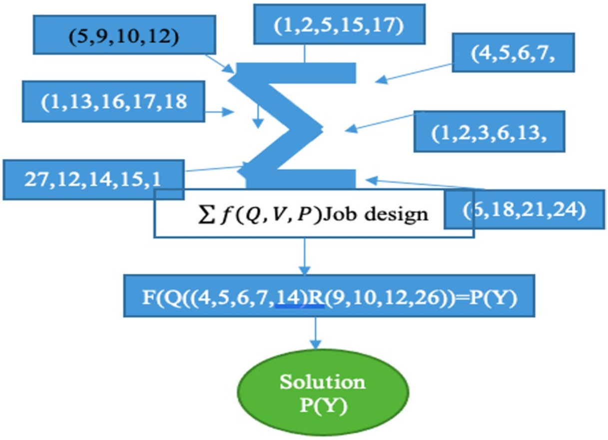


Fig. 6 Model of cluster function associate to job design

6 Open issues and difficulties with possible solutions

6.1 Issues solutions in technology views

A Encounter approaches have a lot of drawbacks and face a variety of obstacles, especially when used in a real-world environment. According to aging experts,

1) **The Availability of Health-Related Data:** the same general condition of a person, and more posed aspects, such as in major health databases, are required to better the earlier digitalization of illness and their pervasive impact in social and economic terms. Collecting many round sets of the same individual or obtaining full recoding and remarking at the level of Serious illness that test the same person at different ages is, however, challenging. As a result, high-performance strategies are required to devise increasingly complex methods of adapting to such constraints. In reality, gathering labeled huge health data and combining it with an actual age is a good idea.

   Estimating is more difficult than collecting age-categorized big health data or identifying anomalies.

   This problem arises as a result of the high rate of human error in calculating true health credit. Human error outnumbers software error.

   It is also difficult to rely on human annotators in large health databases to categorize overall statuses required by enterprises based on their true activity. Despite the fact that various systems have demonstrated their usefulness and accuracy, they all have limitations and difficulties.

   To compensate for this scarcity, a variety of techniques like as cropping, scaling, and cross-checking can be used on the same person. As a result, a single person can take on a variety of roles. Furthermore, the illumination of the health condition may be changed, resulting in a difference in the expert scenarios that will be applied in industries, as well as discussing human will, choices, and personal talents. The amount of health data collected as a result of this technique has increased. As a result, it may be a potential solution to the aforementioned issue.

   Because there is a high rate of human mistake in the labeling process, it is not feasible to rely on human annotators, necessitating the need to assess the picture label.

2) **Via Deep Learning Based On Health Data:**
   Each individual's time libs match with his personal recommendations and skills. Despite its high performance, it necessitates the processing of a vast volume of health data. It's slow, and it necessitates a massive amount of health data. The numerous CNNs perform at least 88 forward passes for each simple individual recode in their pipeline before making a judgment and clustering it to use the system in a real-time or near-real-time application. All of the runner-up approaches have the same limitations. Graphics Processing Units (GPUs) can be used to shorten the time required to complete a task.
3) **The Experts On Aging :** There are several reasons why automated health in proactive care will be used. It is a challenging task. The most fundamental of these is the uncontrollable nature of the aging process, which results in significant variation among illnesses in the same age range, as well as a high reliance on aging characteristics on an individual within an enterprise. However, progress in unconstrained face age estimation has been much slower due to the difficulty of obtaining and classifying massive big health datasets, which are required for training deep networks.
   The great bulk of contemporary aging research is focused with calculating a person's biological age (i.e., the objective age is defined as the time passed from a person's birth date). There are few quantitative ways for measuring the aging outcome. As with all factors, discrepancies are typically connected with additional variances (i.e., lighting, stabilities, skills, satisfaction work performance, etc.).
4) **The Scope Of Ageing And Health Conditions:**
   Nowadays, there are a myriad of business applications for gray amitrole's that assessment and reproduction require to preserve generation by decreasing the cost of firms and society time for constructing new skilled individuals (10–15 years). The deep convolutional neural network (CNN) technology was applied to detect babies using the IIT (BHU) new-born large health database. The correct proportion was determined to be 91.03 percent.
5) **Final Comments:**
   This work studied and addressed a complete assessment of state-of-the-art methodologies for health data analysis applied to economic perspective estimation identification utilizing facial photos. have grown in prominence in recent decades as a result of their potential real-world applications in a number of new enterprises. In this work, the researchers offered multiple solutions to technical challenges, and various large health datasets were utilized to assess the strategies. Large health datasets were utilized to train the evaluation systems. Furthermore, a review of published scientific articles in this field of research was undertaken, with an emphasis on the technique utilized, its performance, and limitations.

6.2 Issues and solutions in the management views

1. The health conditions have great impact on employees' job performance, especially for the elderly employees.
2. There is positive relationship between job tasks and the gender.
3. According to the survey, the female elderly employees are more health than the male.

The limit cluster set based on our experiments size solution is $| S |=m$ we such as $m=2$ based on the experiment.

S (M1)= Within different health condition, the male elderly employees can be signed within different jobs. The more physically demanding jobs can switch the elderly employees to supervision job positions, such as production line supervisors, mentoring and coaching task. For the jobs that have less demanding on physical can sign the elderly employees with more paper works and administrative works, such as management tasks; for the female elderly employees can according to the better health condition compare to the male employees, can signed the employees to more paper work;
S(M2)=within the own wiliness of the respondents, the female elderly employees are more likely to do the management and administrative job tasks, the male employees are more tends to go for the research and technology job tasks Fig. 7.

Based on the previous points covers is that companies should pay more attention to what they offer.

Businesses should pay more attention to what they supply, according to the previous concepts.

The OC is receiving assistance in successfully implementing well fitted model for Criss in association of health of stuff records.

This conclusion also lends validity to previous research that hypotheses and assumption of organization competitive should do.

Finish the health implications on organization and post pandemic restructuration if the company becomes more sustainable.

Improving performance once again, the data shows that health has a significant influence. It's being researched in the context of Chinese SMEs. This will result in great performance.

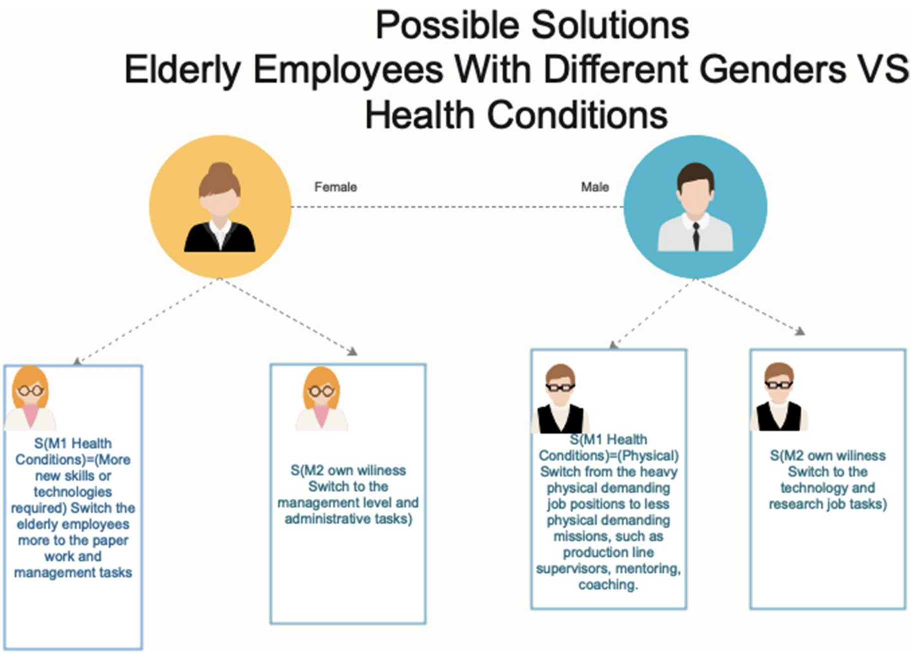


Fig. 7 The possible solutions in management views

This outcome gives a convincing explanation. effect on organizational success and performance

Factors Influencing Long-Term Organizational Excellence This research also supports the idea based on cultural type. As a result, they coexist and complement one another All-in-one solution for improved performance. denotes the tribe Employee interest, communication, and cooperation are all aspects of culture.

Maintaining justice and social equality may contribute to internal coherence.

Possibility of improving market culture's capacity to handle consumer problems in novel ways

To make matters worse, external culture stresses giving what is given health conditions.

Based on Collect data to enhance service/ quality, which in turn improves regulation.

performance. A strong culture must be coupled with a clear focus and homogeneity in a setting that demands solidarity and a shared vision internal organization and society for sustaining of ageing nation.

Make an effort to increase performance instead of retirements be one of the primary motivators for this article to achieve great performance Contributing get good results within\out of organization.

6.3 Compression of the stat of the stat of the art

To the extent of the researcher's knowledge, this is the first study to investigate the role of health in the relationship between the performance of SMEs in China's technocratic and crucial roles. The organization developed a large information that can be progressed in China technique accomplishes preferable entire pattern of organizational members and supply an ideal solution to continue the firm in such crisis with oldy mentality without tracing pandemic as case scenario. Previous research has investigated at how the success of an organization's accounting application effects its organizational health, avoidance and resistance to change, individualism's ability to lead and make judgments, and ganders. Finlay's reaction to a self-learning society Control and Formality Adapting a model from an abstract level of health data to practical and real-life concerns such as labor shortages and the luck of experience, which will be replicated by investigating the sitting studies. Contracting a model to practical and real-life challenges in the realms of large health data health, and big health data management.

Table 4 above is the comprising in management health Vs Parameters Approaches, these three researches has been done in recent years, the researches are focus on the factors affecting the employees' job performance, including the organizational cultural, health conditions and other factors, however, it clearly shows that, these three researches are covering the area of how the organizational cultural affecting the employees job performance, and two of the researches are covering the uncertainty avoidance as the one of the factors and learning cultural as well; only Pawirosumarto [30] covered the

Individualism\ Collectivism as the factor as well as the Thomaidou Pavlidou (2021) covered the Masculinity Vs Femininity and formality and control as the factors. However, comparing this study with the recent studies this research covered all the factors including the health condition which has not covered by any of the studies listed in the Table 3.

Table 4 Comprising management health versus various parameters approaches

	Organizational cultural	Health conditions	Uncertainty avoidance	Individualism\ Collectivism	Masculinity Vs Femininity	Learning Culture	Formality and Control
Proposed approaches	✓	✓	✓	✓	✓	✓	✓
(Thomaidou Pavlidou et al., [39])	✓	-		-	✓	-	✓
(Eniola et al., [14])	✓	-	-	-	-	✓	-
(Mohamed Al Ali et al., [28])	✓	-	✓	-	-	-	-
(Pawirosumarto et al., [30])	-	-	-	✓	-	✓	-
(Song et al., [36, 37])	✓		✓	-	-	-	-

7 Conclusion

The role of big health data analytics (BDHA) in gathering large health data from healthcare systems is expanding. BDHA allows for a dynamic, interactive search of a patient's medical records. One billion records were created in less than two hours. Big health data profiles and meta-big health data were compared using current clinical reporting. Provides simple user interfaces for health-related apps. To create the required hospital-specific large health data, a mix of Hadoop/MapReduce and HBase was employed. Using the approach, one billion (10TB) and three billion (30TB) HBase big health data files may be developed in a week or a month. The performance of simulated medical records was evaluated using Apache technologies in the Hadoop setting. The amount of massive health data generated was limited due to MapReduce's flaws. The intricate ties that huge businesses have. The installation of an encounter-centric big health database was extremely difficult because to health data profiles in a medical system. For this reason, accessories associated with job performance, such as sunglasses and scarves, are popular. What is the demographic profile of the responses for sunglasses photos in terms of genders, current/past job positions, and health conditions. In terms of gender, 66.36 percent of the tokens in the experiments are females, while 33.64 percent are males; the majority of the tokens are healthy, with 66.97 percent, 30.58 percent suffering from common geriatric disease, and the remaining 2.45 percent from occupational disease; in terms of current/past job positions, 20% of the respondents work as accountants, followed by sales and management. There are 157 illnesses included individuals may be diagnosed with one or more illnesses. As a result of medical health professionals watching and analyzing their symptoms, one or more diseases have formed. Mental health issues have been shown to have a negative influence on organizational performance. Anxiety and depression, for example, have been shown to have a direct influence on focus, decision-making processes, and risk-taking behavior in those suffering from anxiety and despair. This may be determined in terms of the employees both for elderly and young, for the organizations, with different job tasks it requires different health conditions, with better health conditions the employees job performance will be high resulting the high organizational performance while reducing the cost of the organizations and increasing the benefits. Machine learning is concerned with strategies for making accurate predictions about future characteristics based on past training. Machine learning approaches that manage large amounts of massive health data need job tusk and computational learning ideas. The learning may expect this new output sequences of parameter to reorganize the organizations with regard to all condition and dispute the health difficulties as a consequence of the new input sequence.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declarations

Conflicts of interest The authors declare no conflict of interest.

Additional Information This research inspired by enormous data situation during pandemic era and shifting to online behavioral for more cover of big data filed.

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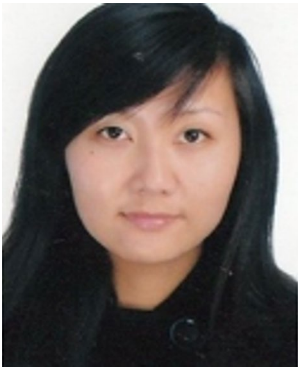

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