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Contents

Satellite Image Processing Using Fuzzy Logic and Modified K-Means Clustering Algorithm for Image Segmentation

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ABSTRACT

Satellite images are useful in providing a real time dynamic picture of the earth and its environment. The large assemblage of remote sensing satellites orbiting the earth provide an extensive and periodic coverage of the planet through the capture of live images round the clock, in turn enabling numerous uses for the benefit of mankind. In the field of satellite image processing, image segmentation is one of the vital steps for extracting and gathering huge amount of information from the satellite images. The basic k-means clustering algorithm is simple and fast in terms of dealing with the required segmentation, but the limitation associated with this clustering is its inability to produce the same result for every run, as the resulting clusters depends on the initial random assignments. In this paper, an enhanced modified k-means clustering algorithm is proposed for the effective segmentation of the satellite images with an objective to overcome the demerits of the k-means by combining fuzzy logic with the membership function. The proposed methodology continuously produces the same result for each run. As an outcome, the experimental results proved that the enhanced k-means algorithm is an effective and more efficient process for the precise and accurate segmentation of satellite images.

KeywordsClustering, Fuzzy logic, Image Segmentation, K-Means, Satellite Imagery.

1. INTRODUCTION

In recent years, along with the breakthrough of machine sciences, image processing has become a field of interest. Image processing has been studied extensively and there have been many applications in practice: as in Medicine, detection and identification of tumor, radiographic imaging, identification of the vascular pathway from the X-ray imaging. One of the many applications cover, perhaps satellite imagery processing to calculate urbanization speed and tightening deforestation and forest cover.

Satellite image processing to calculate the speed of urbanization, forest erosion, deforestation on an area, according to traditional methods from the past was done using drawings, maps, and field trips, but it could not be carried out in areas where human land cannot be set up to check the measurements. Today with modern scientific instruments, we can obtain images from anywhere on the Earth. Through the satellite images captured of a forest, the trial image segmentation (using the K-means algorithm) into different areas, can help us calculate the percentages of changes in the area as depicted by the images over the years. This can in turn aid in concluding urbanization speed, forest cover rates, deforestation rates, change over the period and much more.

The proposed methodology is based on Image segmentation which deals with objects dividing the image into regions that can be considered homogenous according to the most standard feature, such as color, texture, text etc. The result of image segmentation is a set of common areas covering the whole image, or a set of lines mined from the image. Each pixel in the pixel set of a region is similar to each other with attention to some properties or computational attributes such as color sharpness, intensity, and texture. Segmentation techniques are divided into 3 groups: Clustering, edge detection, growing region. Some common clustering algorithms such as K-means is commonly used in image segmentation. Segment of images refers to the process of partitioning a digital image into several different clusters (the pixel set). In this paper, we will be discussing K-Means algorithm, its merits, demerits and proposing a new modified approach to K-Means overcoming the limitations of the traditions K-means model for satellite image processing.

RELATED WORK

There are many ways to modify and improve the traditional K-Means clustering algorithm. It consists of four basic steps: (i) initialization of the clustering, (ii) classification on the data member, (iii) computational stage and (iv) convergence condition. As compared to other stages, initialization stage of the KMeans clustering is the one in which most of the modifications and improvement have been performed. The detailed survey of the previous work on modifications on the K-Means clustering algorithm is shown in Table 1 below.

Table 1. Prior Related Work on K-Means Clustering Algorithm

Reference, Author, Year	Modifications on the traditional K- Means Clustering Algorithm
[1] J.B.McQueen, 1967	Suggested a learning strategy to determine a set of cluster seeds for segmentation.
[2] J.Tou and R.Gonzales, 1974	Proposed simple cluster seeking method.
[3] Y. Linde, A. Buzo, R. M. Gray, 1980	Proposed binary splitting method for segmentation.
[4] G. P. Babu, M. N. Murty, 1993	Suggested method of genetic programming based near optimal seed selection. In this, the selection of the size of the population, mutation and crossover probabilities influence on the result
[5] C.Huang, R. Harris, 1993	Based on principle component analysis, proposed the direct search binary splitting method
[6] I. Katsavounidis, C. C. J. Kuo, Z. Zhen, 1994	Suggested a method starts with selection of a point as the first seed on the edge of the data. The point which is furthest from first seed is consider and selected as the second seed.
[7] M. B. A. Daoud, S. A. Roberts, 1996	Introduced a method to divide the entire data into two different groups and the points are randomly distributed in the group.
[8] P. S. Bradley, U. M. Fayyad,1998	Proposed a method for choosing the most centrally located instance as the first seed.
[9] A. Likas, N. Vlassis, J.J. Verbeek, 2003	Proposed a global K means algorithm in which gradually increase the number of seeds till K is found that is till convergence
[10] S. S. Khan, A. Ahmad, 2004	Introduced a centroid initialization method based on a density- based multi scale data condensation. In this method, the density of the data at a point is estimated, and then sorting the points based on their density.

METHODOLOGYK-means Clustering

K-Means is a very important algorithm and is commonly used in clustering techniques. The K-means algorithm takes the input parameter K and divides a set of n objects in K clusters, the homology in n clusters is high while homology out of clusters is low. Cluster homogeneity is measured when evaluating the mean value of these objects in the cluster which then can be observed as the "focus" of the cluster. The algorithm handles the following: it randomly selects one K object, one out of these points represent a cluster average or cluster data center. For the objects left, each object will be assigned to the cluster that it is most closely based on distance between object and cluster mean. Then the average cluster will be recalculated for each cluster. This treatment will be repeated until the standard convergence function jars.

The purpose of the K-means algorithm is to generate K data sets {C 1 , C 2 , ..., C k } from a data set containing n objects in d space X i = {x i1 , x i2 , ..., x id }, i = 1 ÷ n, such that the standard function is given by (1):

$$E = k\ i = 1 \sum x \in C \quad |x - mi|2\ \mathbf{min} \qquad \mathbf{(1)}$$

'|x - mi|' is the Euclidean distance between Data point x and center

$\{m1, m2, m3, , mk\}$ mi is the center of the cluster C

$\{C1, C2, C3,, Ck\}$ is a set of clusters

'k' is the number of clusters, cluster centers.The Algorithm for traditional K-means is given below.

Begin

1. Initialization:

Randomly selects the centroid for the K cluster. Each cluster is represented by the center of the cluster.

2. Distance calculation:

Calculate the distance between objects to K hearts (usually Euclidean distance) using (1):

$$Dk \sqrt{\sum_{i=1}^{n}(xi - mj)} \qquad \mathbf{(2)}$$

For each point (1 ≤ i ≤ n), calculating its distance to each center (1 ≤ j ≤ k). Then find the closest focus for each point and group them into nearest groups.

3. Update focus:

For every 1≤ j ≤ k, update the cluster focus mj by identifying Averages plus data object vectors using (2).

$$vj = (1/cj) \sum_{i=1}^{Cj} xi \qquad \mathbf{(3)}$$

here, ' cj ' represents the number of data points in jth cluster.

4. Reassign the points near the new group center Group the objects into the nearest group based on the focus of the group.

Stop condition: Repeat steps 2 and 3 until there are no group changes of objectsEnd.

Limitations of Traditional K-means Clustering

The K-means algorithm is proved to be convergent and has a computational complexity of O (tkn) where t is the number of iterations, k is the number of clusters, n is the number of objects of the data set. Usually, k << n and t << n end at a local optimization point.

However, the disadvantage of K-means is that it is very sensitive to interference and extraneous elements in the data. Moreover, the quality of data clustering of the K-means algorithm much depends on the input parameters such as the number of K-clusters and K-centered initialization boards. In the case of the initial initialization focus that is too deviated from the weights, the cluster result of K-means is very low, that is, clusters of data is very different from the actual clusters. Hence, there is not one optimal solution to choose input parameters, the most commonly used way out is to experiment with different K input values and then select the best solution.

Proposed Modified K-means Clustering

The K-Means clustering algorithm is widely used for the segmentation of various images such as medical or satellite images for its fast convergence and simplicity. However, the application and performance of the K-means clustering algorithm is still limited due to several disadvantages as indicated in Section II. In this section, modifications on the conventional KMeans clustering algorithm are introduced to overcome the disadvantages and weakness and improve the segmentation performance. For the modification on the K-Means clustering, consider an image which has N data that have to be clustered into n number of centers. Let Xi be the i-th data and Cj be the j-th center with predetermined initial value where i = 1,2,3,4...,N and j = 1,2,3,4,...,n . In this paper, the concept of fuzzy logic is introduced to modify the k-means clustering algorithm. In fuzzy logic, each member has varying membership contrast to crisp logic wherein each member has clearly defined boundary (its membership strictly either 0 or 1). When fuzzy logic applied to the image, each data member can be assigned simultaneously to more than one cluster or group with different degree of membership. The above mentioned process of fuzzy based approach can be obtained based on the membership function as given by (2)

$$m_{ck} = \frac{1}{\sum_{j=1}^{i}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{1}{q-b}}} \quad \textbf{(4)}$$

where dik is the distance from point k to the current centroid djk is distance from point k to other centroid j and q is the fuzziness exponent where the typical value is 1. After assigning the membership for each data in the image, then we have to apply the fitness calculation process for all the data member using (3)

$$F(c_j) = \sum_{k_{ij}}(x_i - c_j)^2 \quad \textbf{(5)}$$

As part of processing the satellite images, we need to consider the color component of the images as the real time images are multichromatic and not monochromatic.

The basic purpose is to segment the colors automatically using the L * a * b * color space and K-means clustering. The whole proposed methodology of processing satellite images can be summarized in the following steps:

Step 1: Read the image
Step 2: Convert the image from RBG color space to L ab *color space. The space L * a * b* consists of a 'L' layer, a '*' color layer, and a 'b *' color layer. All color information is in layers '* a' and 'b *'. The difference between the two colors can be measured using the standard Euclidean distance.
Step 3: Color Classification in Space "* a * b *" K-means clustering.
Step 4: Label each pixel in the image using the result from K-means. For all objects in the input , K-means returns an index corresponding to a cluster. Label each pixel in the image with its cluster index.
Step 5: Create images that are segmented by color. Using the pixel labels, divide the object in the image by color, which will result in three different images.
Step 6: Segment the kernel into a separate image. Then, the output determines that the clustered indexes contain blue objects because K-means will not return the same cluster_idx value each time. This can be done using the cluster center values, rather than a 'a *' and 'b *' values for each cluster.

Assume that the surface color of the objects in the image is a constant property and that the color is mapped to a 2D space
and color. Then, using the K-means clustering algorithm, the cluster of colors has a set of similar pixels. After segmenting the image, each pixel belongs to a single region. These unique areas usually correspond to the whole or part of the actual objects in the image.

EXECUTION RESULTS

The database consisting of satellite images was created to test the proposed algorithm. The proposed algorithms was coded in MatLab 7.10(R2010a) and executed in Intel core i3 system with 2GB RAM. The performance of this algorithm is assessed with both quantitative comparison and visual judgement as shown in Figure 1 and Figure 2.

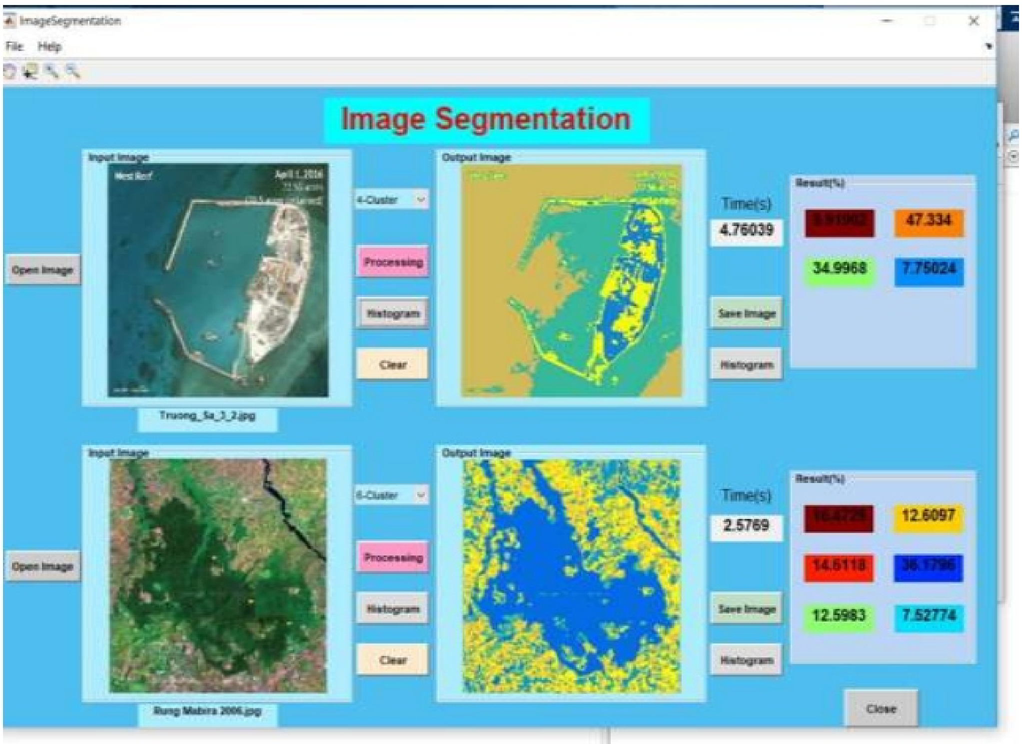

Figure 1. Test Satellite Image

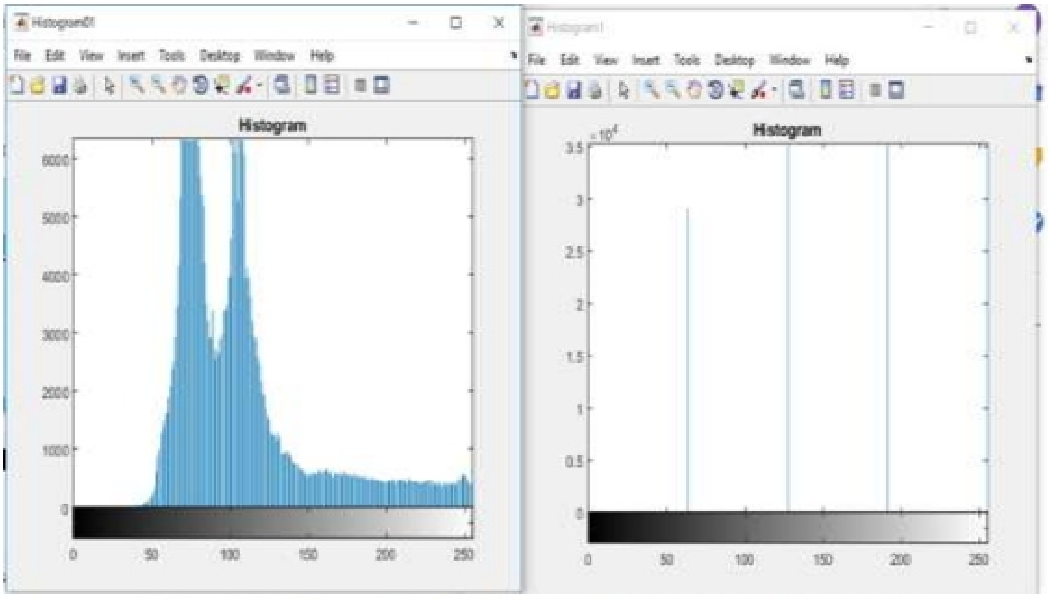

Figure 2. Before and after histogram of the test satellite image

and enhance the segmentation effect.

CONCLUSION

The modified K-Means clustering algorithm for satellite image segmentation was proposed in this paper. The characteristic of the Fuzzy logic is applied to modify the membership function of the traditional K-Means Clustering algorithm. A number of test satellite images were segmented using the proposed algorithm and experimental results proved that the modified algorithm was an effective method for the segmentation of satellite images. This algorithm could segment object precisely, decrease the segmentation time,

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The Anatomization of an IoT Based Aquaponic Farm Model towards the Agronomic Resilience in the Indian Subcontinental Region

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A B S T R A C T

The paper describes most advanced ways of farming in agronomy. The key motive of this paper is to discuss the creation and monitoring of an IoT based aquaponic model on Indian crops such as paddy and its analysis. Aquaponics integrates both aquaculture as well as hydroponics, the planting of plants in groundwater within a circulation system. The result is beneficial products such as fish and crops as well as reducing nutrient pollution in aquatic habitats This paper includes automating the PH concentration and maintaining likewise for crops management for hence better results such as more yield and more income.The primary mechanism is to control the flow of water between the fish pond and the plant beds. The water usage will be 90% lower than the conventional way of farming. More growth will be seen because plants will face ample amounts of nutrients every time.

Keywords Agriculture, Aquaponic, IoT.

INTRODUCTION:

Aquaponics is a symbiotic combination of two food production fields: (1) aquaculture, the practice of aquaculture; (2) hydroponics, the planting of plants without soil. Aquaponics integrates both within a circulation system. The regular circulating aquaculture system filters and removes organic matter ("debris") that accumulates in the water, keeping the water clean for fish. However, aquaponic system filters out nutrient-rich contaminants using a vegetable container. The result is beneficial products such as fish and vegetables as well as reducing nutrient pollution in aquatic habitats.[1] This paper includes automating the PH concentration and maintaining likewise for crops management for hence better results such as more yield and more income.[2] The paper also include the analysis of the data extracted from experiments in Indian crops such as Athyrium filix-femina , Raphanus sativus and Oryza sativa.

SYSTEM DESIGN

The step consists of many components required for a proper farming of fishes and the crops. The fishes excreta fertilize the water which is then pumped to the plant nourishment.

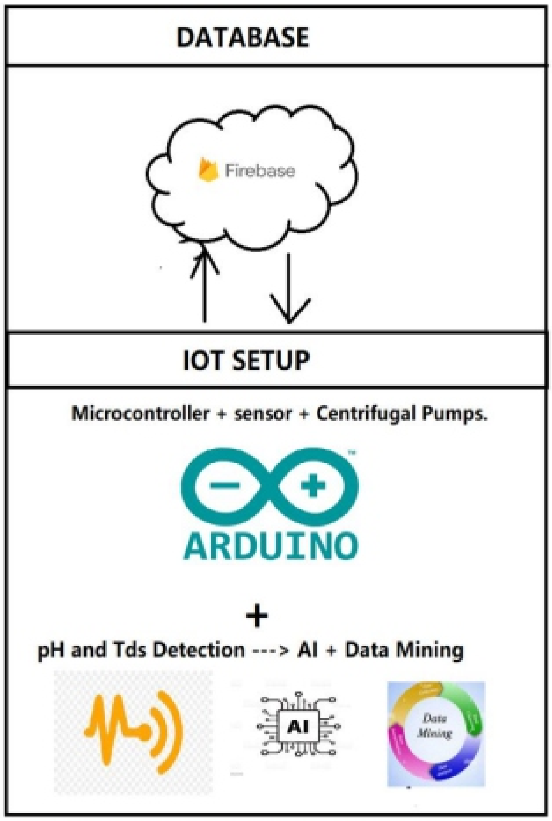


Figure 1. Architecture of the proposed IoT system

IoT Setup

The IoT setup is very essential for this project as the main objective of the paper is to demonstrate this. It contains arduino uno and esp8266 for interfacing.The arduino is used for all data extraction and the esp8266 is used for communication with the internet. The IoT setup consists of various sensors such as - Tds, pH, temperature and humidity as well as water flow sensors. The arduino extracts the data and activates all the pumps accordingly.

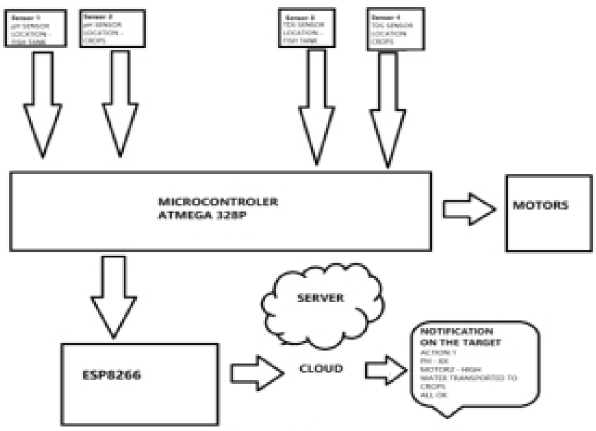


Figure 2. Working of the sensors with IoT.

Real-time database.

The firebase realtime database is used inorder to store and forward the data in target devices through web view and notifications.

The formats are in graphs and GUI for more interactions with the user.

Mechanism of the Bio filter.

In aquaponics, if the extra space in your growth media is not enough for the germs to accumulate, we need to add more space.The biofilter is a really important part of our system. It ensures that plants have enough nutrients to grow healthy while purifying the water for the fish to survive.

The entire aquaponics system is a biological filter. The Vertical, and aquaponics farms to grow our plants we cannot rely on the natural process of bio filtration due to lack of sufficient space but the media-based aquaponics system usually does not require a separate biological filter because it is a reservoir, growing media (expanded clay, rock formations, or lava rock), tank walls, and other surface areas provide ample space for germs to accumulate.

The biofilter is an exceptional extension of your aquaponics system. It's far and away a critical part of our aquaponics device as it guarantees that your plants get the nitrates to grow at the same time as purifying fish water.Germs get attached to the surface of the biofilter. Biofiltration in aquaponics occurs in three main steps. This process is a widespread set of aquaponics. The system or steps might also range relying on your biofilter design.

1. An air pump pumps water from a fish tank to a biological filter.
2. Within the biofilter, water flows through the nitrification procedure. There were useful microorganisms that helped to transform ammonia and nitrites into nitrates.
3. Nutritious water flows from the organic filter to the flowers, in which the plant roots absorb the nutrients while purifying the water earlier than returning to the fish tank.Top biofiltration is critical for the chemical stability for your aquaponics device. That's why it's vital to apprehend the function of the herbal clear out in aquaponics so you realize if your system needs a natural filter out.[4]

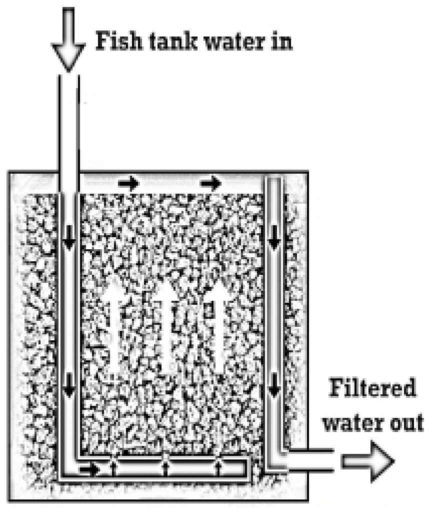


Figure 3. the diagram of the bio filter.

Ph and Tds mechanism.

The ph and tds are kept in two sites in the module one in the planting area and other in the fish pond the both data are taken simultaneously in order to attain a differential data. When the pH of the fish pond is higher the water is sent to the planting area and when the pH of the planting area is neutral it is sent back to the fish pond. Same mechanism goes with TDS.TDS formulas for interfacing with arduino. Total Dissolved Solid = Correlational Factor * Electrical Conductivity .[5]

Water Recirculating System.

There are many designs of aquaponics systems made , however one system is famous for its simplicity. Which is known as CHOP representing the steady peak One Pump program. This system consists of a hydroponic plant mattress, a fish aquaculture tank and a sump tank. The submersible water pump is set up within the sump tank to continue turning in water to the fish tank constantly even as the water is fed to the growing bed via a drain pipe. The accumulated water in the hydroponic beds is then discharged again into the sump tank with a bell siphon. The bell siphon is a popular tool used for flood structures and drains. With CHOP, the water stage within the fish tank is maintained and as a consequence considered to be the most green system to apply and gets rid of stress on fish due to water fluctuations.

additionally, it makes use of the handiest one pump to deliver constant water flow for this reason saving power compared to maximum pump structures.[11,12]

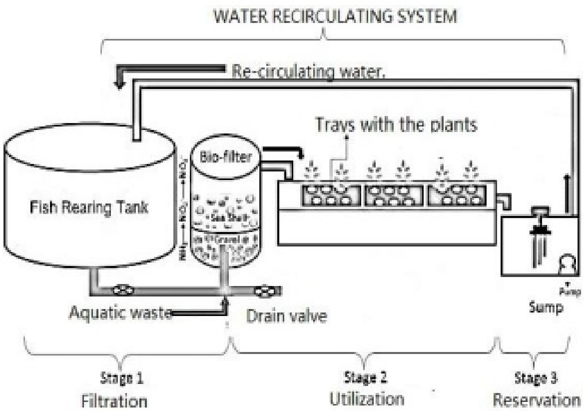


Figure 4. The Water Recirculating System.

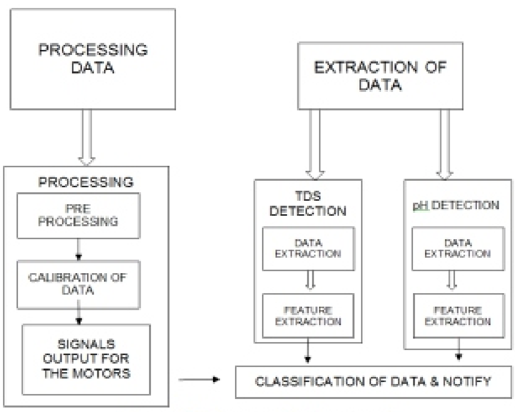


Figure 5. Proposed framework.

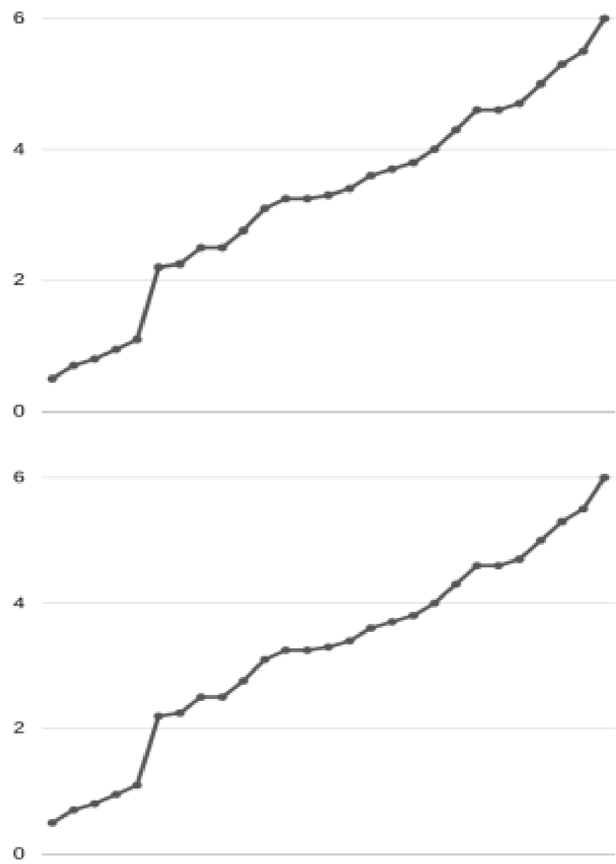
EXPERIMENTAL DATA AND ANALYSIS OF RESULTS.

Impact of Aquaponics in Various Indian Crops

Aquaponics was seen quite successful in Indian crops as the growth of the fishes as well as for the Indian crops was quite well observed.

Figure 6. The automated aquaponic farm model Athyrium filix-femina

The growth of Athyrium filix-femina was recorded and presented below in cms of the plant's size with a time period of 2 weeks.



Graph 1. The growth of the crops in the automated aquaponic farm.

Figure 7. The automated aquaponic farm model Raphanus sativus.

Impact of Paddy in Aquaponics.

The Paddy requires 68° to 82° F, pH Requirement = 6 to 7, Nutrient Requirement: Medium to High[9,10] and which can be attained by aquaponics and we can get a good yield.But due to the high infrastructure cost of paddy in aquaponics it is not tried on a large scale.The experimentation of paddy was done on a small scale with automations but we did not receive good yield

Figure 8. aquaponics farm model of paddy.

Crops in Aquaponics

Aquaponics holds a record of various crops that can be grown in it which include cucumbers, shallots, tomatoes, lettuce, capsicum, red salad onions, snow peas, carrot,cabbage,strawberry.

Table 1. The crops in aquaponics.[3]

CROPS	NUTRITION REQUIREMENT	pH	TEMP (F)	REMARKS
Lettuce (Lactuca sativa)	LOW	6.0-6.2	60°-70°	EASY
Mint (Mentha)	LOW	6.5-7.0	65 ° to 70°	MODERATE
Tomato (Solanum lycopersicum)	HIGH	5.5 to 6.5	65°F to 85°	MODERATE
Chili (Capsicum frutescens)	MEDIUM TO HIGH	5.5 to 6.5	60° to 75°	HARD
Cabbage (Brassica oleracea var.capitata)	HIGH	6.2 to 6.6	45° to 75°	EASY

Fishes to be used in Aquaponics

The fishes that are very hard and which secrete more excreta can be used in aquaponics.

Table 2. Fish that breathe air and which are tested during the experimentation [8]

I. Anabas	This Anabas fish is also called mountaineering Perch, it eats meat and will grow up to fifteen to 30 CM in duration in the wild. The planting season is 6 months to one year. It has the capability to survive without water for 6 to eight hours.
II.Pangasius	Pangasius is also referred to as Shark catfish, It grows to size (20 to 30 CM or extra) in clear water. The planting duration stages from 6 months to one yr.
III.Gourami	This fish is likewise referred to as hiking Gouramis, it's miles smooth and pleasant. it will develop to a size (20 to 30 CM or greater) in tall water. It can be harvested in 12 to 24 months.

Figure 9. The fishes that were used in the experiment for aquaponics.(Anabas testudineus)

Comparison between Round and Square NFT Channels.

The square channels are more considered as they offer a higher surface area to volume ratio and thus better movement and gas exchange along the length of the channel and they also offer greater stability than the round channels but they are very hard to construct and very expensive in the market. The round channels are very easy to find anywhere but the stability and mobility is a big disadvantage for them.[6]

Analysis of the Data in IoT.

The working of the IoT is quite complex as due to the variation of data in various parameters. The actual results of the proposed frameworks have been listed below.

PH1 FISH TANK	PH2 CROP AREA	RESULT
HIGH	HIGH	WATER WILL BE SENT TO OTHER TANK FOR LATER USE
HIGH	LOW	WATER WILL BE SENT TO CROPS AND THE CROPS WATER WILL BE SENT TO FISH TANK
LOW	HIGH	WATER WILL STAY AS IT IS AND ALL THING IS PERFECT
LOW	LOW	WATER STORED IN THE TANK WILL BE SECREATED TO THE CROP AREA

Table 3. The actions taken by the computer (microcontroller) in specific parameters listed above.

The Tds sensor was connected with the microcontroller and the data that were observed is listed below. The microcontroller recorded everything and presented the data in the serial monitor so that the data could be analyzed properly

Figure 10. The TDS reading on the serial monitor.

The pH sensor was connected with the microcontroller and the data that were observed is listed below. The microcontroller recorded everything and presented the data in the serial plotter .

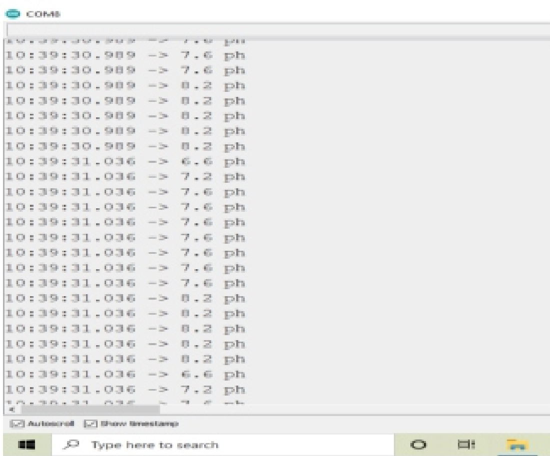


Figure 11. The pH reading on the serial monitor.

Graph 2. The pH reading on the serial plotter.

The notification of the working of the system is sent by two mediums - email and message and both illustrations are provided below

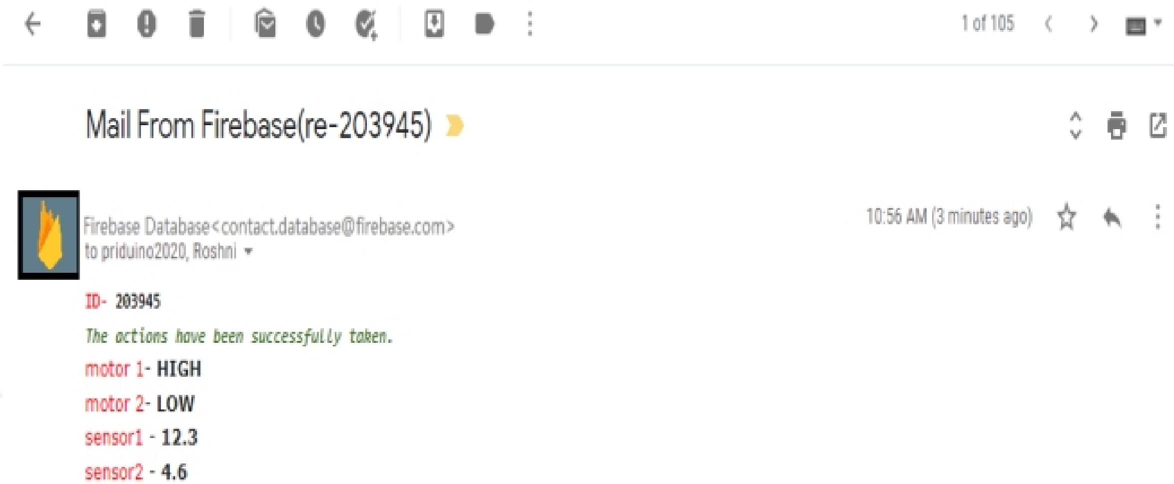


Figure 12. The notification email from the firebase of actions.

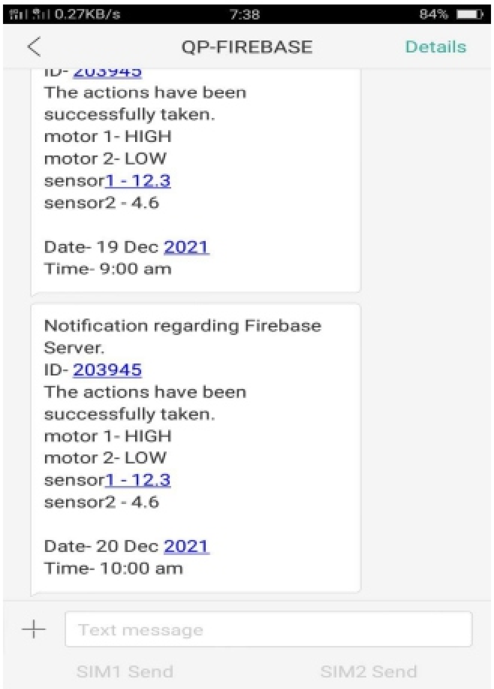


Figure 12. The notification message from the firebase.

CONCLUSION

In this study, the automation of aquaponic farms was conducted. Farmers will see an increase in profits as crop yields increase, as well as a doubled income from fish. Fertilizer costs will be reduced, which will benefit The amount of water used will be 90% less than in traditional farming.[7] No chemicals will be employed, and only fish excreta will be used, resulting in a fully organic yield.Plants will grow faster since they will be exposed to abundant amounts of nutrients at all times.

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Digital Literacy Skills and Engagement on the Advanced Classroom Tools and Soft-Wares of Elementary Teachers in Relation to their Coping Skills

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ABSTRACT

This study aimed to measure the relationship between Digital literacy skills of Elementary Teachers and their extent of engagement on the use of advanced digital classroom tools and software, Degree of digital literacy skills of Elementary Teachers and their coping skills, and the extent of engagement of Elementary Teachers on the use of the advanced digital classroom tools and software. The researcher utilized three survey questionnaires on Digital Literacy, Teachers' Engagement on Digital Classroom Tools and Software, and Teachers' Coping Skills. The following survey was conducted through google forms, 60 Elementary Teachers from 10 selected private schools in Cavite, Philippines was purposefully chosen to be the respondents of this study, hence, Descriptive correlation method was employed. In the light of statistical analysis and the findings of this study, the following conclusions and recommendations were drawn: First, Elementary Teachers have a high degree of literacy in performing tasks successfully in a digital environment, with digital meaning information represented in numeric and basically for utilization through a computer. Second, Elementary Teachers in selected private schools in Cavite, Philippines moderately engaged on the Use of Advanced Digital Classroom Tools and Software. Third, Elementary Teachers have a moderate level of coping skills which involves steady value or religious belief system, problem solving, social skills, health-energy, and commitment to a organization. Fourth, there is a significant relationship between the digital literacy skills of Elementary Teachers in terms of operational skills and creative use and their extent of engagement on the use of advanced digital classroom tools and software. Fifth, there is a significant relationship between the digital literacy skills of Elementary Teachers in terms of information navigation and creative use and their coping skills. Sixth, there is a significant relationship between the extent of engagement of Elementary Teachers on the use of advanced digital classroom tools and software and their coping skills. The overall findings influenced the researcher to develop a Technology Enrichment Program to further enhance the Degree of Digital Literacy Skills, Extent of engagement on the use of Advanced classroom tools and software, and the coping skills of Elementary Teachers who participated in this study.

Keywords Coping Skills, Digital Literacy, extent of engagement on digital tools and software.

1. INTRODUCTION

Today's world of a changing workforce, rapid developments in technological know-how and elevated global opposition suggests that learning is extra and critical than before most especially during this time where COVID 19 forces everyone to engage into utilizing technology to restrain and control people from going out of their houses for work, schooling, leisure and other "normal" activities that involve face to face interaction and social exposure.

This type of prohibition is one of the best precautionary measures in preventing the rapid spread of the virus, in this way, people will be protected from acquiring and passing through the virus. This compelling factor and situation encourages everyone to cope to the digital technology advancement particularly those who are involved in education. Educators are in any way expected to become proficient and able to cope with the recent changes in technology. At all levels, our education system is recognizing the need to change to meet the demands of a rapidly changing digital community. The need to have a long-term goal for education that gives assurance that all students experience agreeable result and have the knowledge, skills, abilities and competencies to be successful in the 21st century was never more significant. The "new normal" set up in the Educational System must be considered because of the unexpected and inevitable effect of the pandemic. The success of the students depends upon the Teachers Literacy in most areas of the teaching process that can be related to the significant utilization of digital technology to this present times. Many of us will already have an appreciation of the term literacy and what is ability to be literate. In the conventional interpretation it is the capacity to be in a position to study and write. This description predominantly bounces back the time in which it came in to frequent use and the presiding equipment for getting access to and communicating understanding and comprehending beyond oral discourse, i.e. written and printed textual content in physical forms. Teachers who are structuring digital literacy skills identify the fundamentals of Internet peril and safety such as creating strong passwords/ form of identification, understanding and using privacy settings, and knowing what to share or not on social media. The competency of teachers on how to use this technology in the teaching-learning process has a significant impact on using them effectively. Although this study did not examine the attitudes of teachers, but this issue is vital for teachers on the use of technology. Those who have more years of experience and knowledge are more positive, because their attitude has also improved, which was a very important result because it will show that teacher training is an important factor in the effective use of Technology in the teaching and learning process. The aim of this research study is to scrutinize Elementary Teachers' digital literacy skills and engagement to serve as basis for enhanced technology-rich teaching program. The focus of this paper is on upgrading teachers' digital literacy to effectively improve their teaching to accommodate diverse needs of learners and the challenges they experience on their process of learning. ([14], 2018). Specifically, the following questions are to be answered by this research study: 1. What is the degree of Digital Literacy Skills of Elementary Teachers on the selected Private Schools in Cavite? in terms of the following: Operational Skill, Information Navigation, Social Use, Creative Use, Mobile and Computer Navigation, Digital Awareness 2. What is the extent of engagement of Elementary Teachers on the use of advanced Digital classroom tools and software? in terms of Video Conference and Collaboration Platform, Course Authoring Tools, Audience Engagement Tools, Learning Management System, Survey Tools, Screen Recording and Video Editing,Presentation Applications, File Sharing, Digital Notebook and Calendar Timetable, 3. What is the level of Teachers' coping skills? 4. How significant is the relationship between Digital literacy skills of elementary teachers and their extent of engagement on the use of advanced digital classroom and soft wares, Degree of digital literacy skills of elementary teachers and their coping skills, and The extent of engagement of elementary teachers on the use of the advanced digital classroom tools and software and their coping skills? 5. Based on findings of the study, what technology enrichment program may be proposed? This study will fulfill the need for the improvement of Digital Literacy Skills and Engagement of Elementary Teachers and their coping skills. This will also mean establishing strong digital literacy foundation among primary teachers and motivate primary pupils to positively engage in the digital technology use especially now that we are all facing COVID 19, where technology is a major part of our day to day living experiences particularly in learning/ education.

RESEARCH DESIGN

The descriptive correlation method was employed in this research study with the comprehensive description of the measure of relationship between the variables; degree of Digital Literacy Skills of Elementary Teachers and their extent of engagement on the use of advanced Digital classroom tools and software, their coping skills and the degree of Digital Literacy Skills of Elementary Teachers and their coping skills and the extent of engagement on the use of advanced Digital classroom tools and software of Elementary Teachers. One of the ways to secure a valid result from this study is through utilizing survey. In a survey, Elementary Teachers from 10 selected private schools in Cavite, Philippines were asked questions about the topic of concern. Through Descriptive Correlation method, each variable was critically and carefully examined and discussed as required in this study.

INSTRUMENTATIONThe researcher utilized three survey questionnaires to fulfil the purpose of this study. The first research instrument is the Digital Literacy Questionnaire. This questionnaire is(ADAPTED FROM Jeong-Bae Son, Copyright 2015 and Alexander J.A.M. van Deursen, Ellen J. Helsper and Rebecca Eynon, Copyright 2014 https://www.lse.ac.uk/). The second research instrument is the Questionnaire on Teachers' Engagement on Digital Classroom and Software (Adapted from CLASSTER, copyright 2020 www.classter.com). The third research instrument is the Questionnaire on Teacher's Coping Skills, Adapted from: [3]. (2013). COPE Inventory. Measurement Instrument Database for the Social, Retrieved from www.midss.ie .

STATISTICAL ANALYSIS OF DATA To find meaning in the data gathered, this study was subjected to the following statistical formula: 1. To determine the degree of digital literacy skills of Elementary Teacher's, frequency count, weighted mean and standard deviation were used, 2, To identify the coping skills of Elementary Teachers, frequency count, mean and standard deviation employed. 3. To test the significant relationship between teachers' digital literacy skills and their engagement, teacher's digital literacy skills and their coping skills, and teacher's engagement on the use of advanced digital classroom tools and software and their coping skills, Pearson r was applied.

RESULTS AND DISCUSSIONS

Digital Literacy Skills of Elementary Teachers in Private Schools

Table 1: Summary Table on Teachers' Digital Literacy Skills

Teachers' Digital Literacy Skills	Weighted Mean	Verbal Description	Rank
1. Social Use	4.64	Very Highly Literate	1
2. Operational Skills	4.55	Very Highly Literate	2
3. Digital Awareness	4.21	Highly Literate	3
4. Mobile and Computer Navigation	4.19	Highly Literate	4
5. Creative Use	3.45	Moderately Literate	5
6. Information Navigation	2.85	Moderately Literate	6

This table shows the Summary Table on Digital Literacy Skills of Elementary Teachers on the selected Private Schools in Cavite, Philippines. It shows an overall weighted mean of 4.35 (highly literate) with a low standard deviation of 0.58 between items, considered as homogenous which can be interpreted that each Elementary Teacher response in each item is nearly similar to each other. The results indicate that Elementary Teachers have a high degree of literacy in performing duties successfully in a digital environment, with digital meaning records represented in numeric shape and particularly for use through a computer. Two among the six items falls on the very highly literate level, two falls on highly literate level and another two falls on the moderately literate level. The results presented on the table is supported by the statement of ([1], 2015) that as new literacies include digital and media technologies expand, preparing students to comprehend and adapt to these literacy demands is crucial to present and future assumptions for and work. As a matter of fact, teachers may recognize with previous models of literacy that are paper and pencil bound; nevertheless, new conceptions continually involve changing views of reading and writing, particularly with the occurrence of the Internet. These new literacies is made up of innovative text formats (multiple media or hybrid texts; new reader expectations (reading nonlinearly;) and new activities.

Extent of Engagement of Elementary Teachers on the Use of Advanced Digital Classroom Tools and Software

Table 2: Summary Table on the Extent of Engagement of Elementary Teachers on the Use of Advanced Digital Classroom Tools and Software

Digital Classroom Tools and Software	Weighted Mean	Verbal Description	Rank
1. Survey Tools	3.99	Highly Engaged	1
2. Video Conference and Collaboration Platform	3.98	Highly Engaged	2
3. File Sharing	3.52	Highly Engaged	3
4. Presentation Applications	3.14	Moderately Engaged	4
5. Learning Management System	2.94	Moderately Engaged	5
6. Screen Recording and Video Editing	2.45	Fairly Engaged	6
7. Digital Notebook and Calendar-Timetable	2.43	Fairly Engaged	7
8. Course Authoring Tools	2.38	Fairly Engaged	8
9. Audience Engagement Tools	2.35	Fairly Engaged	9

Table 2 shows the summary table on the extent of engagement of elementary teachers on the use of advanced digital classroom tools and software. It shows average (weighted mean of 3.02, moderately engaged) with a low standard deviation of 0.71 between items, considered as homogenous which can be interpreted that each Elementary Teacher response in each item is nearly similar to each other. The result indicates that Elementary Teachers in selected private schools of Cavite are moderately engaged on the Use of Advanced Digital Classroom Tools and Software.

According to ([7], 2015) There is indisputable evidence that digital equipment, tools and resources can, where effectively used, lever up the speed and profoundness of learning for primary and secondary age learners. There is suggestive evidence that the same can be said for some aspects of literacy, especially writing and comprehension. Digital technologies appear to be pertinent that intends to improve basic literacy and numeracy skills, especially in primary settings.

Level of Teachers' Coping Skills

Table 3: Summary Table on Elementary Teachers Level of Coping skills

Items	Weighted Mean	Verbal Description	Rank
1. Positive Reinterpretation and Growth	4.41	High Coping Skills	1
2. Mental Disengagement	3.30	Moderate Coping Skills	11
3. Focus on and Venting of Emotions	3.44	Moderate Coping Skills	10
4. Use of Instrumental Social Support	3.86	High Coping Skills	5
5. Active Coping	4.09	High Coping Skills	4
6. Denial	2.61	Moderate Coping Skills	13
7. Religious Coping	4.10	High Coping Skills	3
8. Humor	2.95	Moderate Coping Skills	12
9. Behavioral Disengagement	2.58	Moderate Coping Skills	14
10. Restraint	3.55	High Coping Skills	9
11. Use of Emotional Support	3.64	High Coping Skills	6
12. Substance Use	1.15	Least Coping Skills	15
13. Acceptance	3.57	High Coping Skills	8
14. Suppression of Competing Activities	3.60	High Coping Skills	7
15. Planning	4.23	High Coping Skills	2

This table shows the level of Elementary Teacher's coping skills. It shows average (weighted mean of 3.40, coping skills) with a low standard deviation of 0.19 between items, considered as homogenous which can be interpreted that each Elementary Teacher response in each item is almost alike to each other. The result indicate that Elementary Teachers have a moderate level of coping skills which involves steady value or religious belief system, problem solving, social skills, health-energy, and commitment to a social organization. (Johnson, 2016) have mentioned that Teachers' attitudes and beliefs are crucial factors in determining the role and effectiveness of technology in classrooms. Attitudes and beliefs about both educational technology and pedagogy in general will ultimately influence how teachers implement technology. In the sections, we discuss these issues and ways to promote positive attitudes that can optimize technology use.

Relationship between *Digital Literacy Skills of Elementary Teachers and the Extent of Engagement on the Use of Advanced Digital Classroom* Tools and Software

Table 4.1 Summary Table on Pearson's r Test of Relationship between Digital Literacy Skills of Elementary Teachers and the Extent of Engagement on the Use of Advanced Digital Classroom Tools and Software

Correlated Variables		Computed r	Critical Value at 0.05	Significance	Decision
Digital Literacy Skills	Digital Classroom Tools and Software				
Operational Skills	Digital Classroom Tools and Software	0.329	0.259	Significant	Reject Ho
Information Navigation		0.119	0.259	Not Significant	Accept Ho
Social Use		-0.128	0.259	Not Significant	Accept Ho
Creative Use		0.261	0.259	Significant	Reject Ho
Mobile and Computer Navigation		0.065	0.259	Not Significant	Accept Ho
Digital Awareness		-0.059	0.259	Not Significant	Accept Ho

N= 60 df = (N-2) 58

The data in table 4.1 shows that there is a relationship between the digital literacy skills of Elementary Teachers in terms of operational skills since the computed r (-0.329 is greater than the critical value 0. 259 at 0.05 level of significance. There is also a significant relationship in of creative use since the computed r (-0.261 is greater the critical value 0.259 at 0.05 level of significance), and their extent of engagement on the use of advanced digital classroom tools and software thus, rejects the null This implies that Elementary Teachers' Digital skills in terms of operational skills and creative use has a great impact on their extent of their involvement in the use of digital classroom tools and software. On the other hand, the data in table 4.25 shows that there is no relationship between the digital literacy skills of Elementary Teachers in terms of information navigation since the computed r (0.119 is lower than the critical value 0.259 at 0.05 level of significance), social use since the computed r (-0.128 is lower than the critical value 0.259 at 0.05 level significance), mobile and computer navigation since computed r (0.065 is lower than the critical value 0.259 at 0.05 level of significance), digital awareness since the computed r (-0.059 is lower than the critical value 0.259 0.05 level of significance), and their extent of engagement on the use of advanced digital classroom tools and software thus accepts the null hypothesis. This implies that Digital Literacy skills in terms of information navigation, social use, mobile and computer navigation and digital awareness has no strong association on the extent of their involvement in the use of digital classroom tools and software. The result obtained by this study is supported by the vantage point of ([10], 2020)that Digital literacy is a main element in education today. The future success of educators and students depends on them becoming digitally literate. This includes creating abilities and information that empower them to securely explore and observe all shapes of advanced technology

Digital Literacy Skills of Elementary Teachers and their Coping Skills

Table 4.2 : Summary Table of Pearson's r Test of Relationship between Digital Literacy Skills of Elementary Teachers and their Coping skills.

Correlated Variables		Computed r	Critical Value at 0.05	Significance	Decision
Digital Literacy Skills	**Coping Skills**				
Operational Skills	Coping Skills	-0.060	0.259	Not Significant	Accept Ho
Information Navigation		0.597	0.259	Significant	Reject Ho
Social Use		0.011	0.259	Not Significant	Accept Ho
Creative Use		0.319	0.259	Significant	Reject Ho
Mobile and Computer Navigation		-0.081	0.259	Not Significant	Accept Ho
Digital Awareness		0.109	0.259	Not Significant	Accept Ho

N= 60 df = (N-2) 58

The data in table 4.2 shows that there is a significant relationship between the digital literacy skills of Elementary Teachers in terms of Information navigation and their coping skills since the computed r (0.597), creative use and their coping skills since the computed r (0.319) is greater than the critical value 0.259 at 0.05 level of significance), thus, rejects the null hypothesis. This implies that Elementary Teachers' Digital literacy skills in terms of information navigation and creative use has a strong effect on their coping skills. On the other hand, the data further reveals that there is no significant relationship between the digital literacy skills of Elementary Teachers in terms of operational skills and their coping skills since the computed r (-0.060), social use since the computed r is (0.011), mobile and computer navigation since the computed r is (-0.081), digital awareness since the r is (0.109) is lower than the critical value 0.259 at 0.05 level of significance, thus, accepts the null hypothesis. This implies that Elementary Teachers' Digital Literacy skills in terms of operational skills, social use, mobile and computer navigation and digital awareness has no remarkable impact on their coping skills. The results obtained are proven by the assertion of (Johnson, 2016) that Teachers' attitudes and beliefs are pivotal components in deciding the part and adequacy of innovation in classrooms. Attitudes and beliefs approximately both instructive innovation and instructional method in common will eventually impact how instructors execute innovation in terms of digital technology. In the following sections, we discuss these issues and ways to promote positive attitudes that can optimize technology use.

The Extent of Engagement of Elementary Teachers on the Use of Advanced Digital Classroom Tools and Software and their Coping Skills

Table 5: Result of Pearson's r Test on the Relationship between The Extent of Engagement of Elementary Teachers on the Use of Advanced Digital Classroom Tools and Software and their Coping Skills

Correlated Variables		Computed r	Critical Value at 0.05	Significance	Decision
Advanced Digital Classroom Tools and Software	**Coping Skills**				
Advanced Digital Classroom Tools and Software	Coping Skills	0.310	0.259	Significant	Reject Ho

N= 60 df = (N-2) 58

Table 5 shows that there is a significant relationship between the extent of engagement of Elementary Teachers the use of advanced digital classroom tools and software and their coping skills since the computed r (0.310 is greater than the critical value 0.259 at 0.05 level of significance), thus, rejects the null hypothesis. This implies that the extent of engagement of Elementary Teachers on the use of advanced digital classroom tools and software has a strong connection on their coping skills. Faculty member attitudes toward technology, fear factors and complexity issues, lack of time and support, limited access, inadequate faculty development opportunities, and lack of organizational support have all been identified as major barriers to the infusion of into teacher preparation programs ([13], 2015)

CONCLUSIONS

Based on findings of the study, the following conclusions were drawn: 1. Elementary Teachers have a high degree of literacy in performing duties successfully in a digital environment, with digital meaning records represented in numeric shape and particularly for use through a computer. 2. Elementary Teachers in selected private schools of Cavite, Philippines are moderately engaged on the Use of Advanced Digital Classroom Tools and Software. 3. Elementary Teachers have a moderate level of coping skills which involves steady value or religious belief system, problem solving, social skills, health-energy, and commitment to a social organization., 4.There is a significant relationship between the digital literacy skills of Elementary Teachers in terms of operational skills and creative use and their extent of engagement on the use of advanced digital classroom tools and software. There is no significant relationship between the digital literacy skills of Elementary Teachers in terms of information navigation, social use, mobile and computer navigation and digital awareness and their extent of engagement on the use of advanced digital classroom tools and software., 5. There is a significant relationship between the digital literacy skills of Elementary Teachers in terms of information navigation and creative use and their coping skills., 6. There is no significant relationship between the digital literacy skills of Elementary Teachers in terms of operational skills, social use and mobile and computer navigation and their coping skills., 7.There is a significant relationship between the extent of engagement of Elementary Teachers on the use of advanced digital classroom tools and software and their coping skills., 8. The overall findings influenced the researcher to develop a Technology Enrichment Program to further enhance the Degree of Digital Literacy Skills, Extent of engagement on the use of Advanced Digital classroom tools and software, and the coping skills of Elementary Teachers who participated in this study.

RECOMMENDATIONS: Based on findings and conclusions of the study, the following recommendations are offered: 1.Elementary Teachers must undergo an intensive training on Digital Literacy Skills prioritizing in the areas of Creative Use and Information Navigation must be enhanced as well as in the areas of Digital Awareness and Mobile and Computer Navigation to help them achieve a very highly literacy skills in all of the 6 components of Digital Literacy Skills. 2. Elementary Teachers needs more exposure through hands on experience/ workshop on the use of digital classroom tools and software specifically on the areas that falls on the fairly engaged level such as Screen Recording and Video Editing, Digital Notebook and Calendar Timetable, Course Authoring Tools and Audience Engagement Tools. 3.Elementary

Teachers needs more enlightenment through several programs that helps improve coping skills such as Mindfulness, Wellness Program and other activities related to enhancing coping skills particularly in the areas which falls on Moderate level of coping skills such as Mental Disengagement, Focus on venting of emotions, Denial, Humor and more importantly on the area which falls on Least level of coping skills such as Substance Use. 4. Elementary Teachers ought to receive a comprehensive and explicit training on Digital Literacy Skills in terms of Skills and Creative Use and their Extent of Engagement on the use of Advanced Digital classroom tools and software. 5. School Administrators must be compelled to provide a thorough Faculty Development program for Teachers focusing on Technology Enrichment that will help improve their quality of teaching and to contribute well on their students digital learning experience.

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Predictive Analytics of Selected Datasets using DTREG Data Mining Tool

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A B S T R A C T

Predictive analytics is making a significant wave in healthcare Industry. Predictive analytics is an analytics offshoot which helps to make future predictions, resulting in more informed decisions. Data is central to accurate predictions. Several concepts like Data Mining, (Artificial Intelligence), Machine Learning and statistics need to work in tandem to ensure precise predictions. The main aim of the research work was to analyse the datasets of selected diseases using the DTREG data mining tool. Two datasets namely Alzheimer's and Breast Cancer were taken from a public repository and analysed. Various algorithms namely single tree, decision tree, tree boost, support vector machine and neural network were studied. The results obtained were interpreted to understand which algorithm works best in each case. Also, the important predictors in each study were recorded. Interpretation of Alzheimer's and breast cancer data using DTREG revealed neural network as the best algorithm. The significant predictors for Alzheimer's were estimated as total intracranial blood volume, clinical dementia rating and age, and for breast cancer were uniformity of cell size, cell shape, benign and malignant and clump thickness. Data mining, artificial Intelligence and machine learning can thus be of very good help in determining the line of treatment to be followed by extracting knowledge from such suitable databases.

KeywordsAlgorithms, Alzheimer's, Breast Cancer, DTREG.

1. INTRODUCTION

Predictive analytics is a branch in the domain of advanced analytics. It is utilized in prognosticating the future events. analyzes the current and historical data to make predictions about the future by employing the techniques from statistics, data mining, machine learning, and artificial Predictive analysis can create more efficient and effective health systems. There are many applications of predictive analysis which includes, creating a prognosis score using patient records, genetic screening which can help to determine possible diseases, faster and more accurate interpretation of medical images like X-rays. Since a lot of patient data is available, even from wearables, predictive analysis can also help with accessing crucial patient data of remote patients and predict their hospital visits, admissions, and emergencies (proactive care). Predictive analytics can handle large data sets, for example, cohort data. With predictive analysis, it is possible to establish the general health of a community [1]-[3].

Data mining is a process of computing models or design in large collection of data using the steps - exploration, pattern identification and deployment. It is concerned together with the method of computationally extracting knowledge from vast sets of data. Data mining can be used to extract knowledge by analysing and predicting some diseases. Data mining applications in health care can have wonderful potential and effectiveness. It automates the process of finding predictive information in large databases. Disease prediction plays an important role in Health care data mining is an important task because it allows doctors to see which attributes are more important for diagnosis such as age, weight, symptoms, etc [3]-[8].

In this study, we selected DTREG, an open-source software and worked on data from selected databases. DTREG is a decision tree building software product that can be used for Predictive Modeling (Data Mining) and Forecasting. It can be used to predict values for future observations and also has full support for time series analysis.It accepts a dataset in the form of table containing number of rows, whose columns represent attributes/variables. One the variables is the ‘‘target variable’’ whose value is to be modeled and predicted as a function of the ‘‘predictor variables’’. The DTREG analyzes the data and generates a model showing how best it predicts the values of target variable based on the values of predictor variables. It builds classification and regression decision trees, neural networks (NN), support vector machine (SVM), gene programs, K-means clustering, discriminant analysis and logistic regression models that can describe data relationships. The significant features of DTREG includes ease of use, can build classification and regression trees, automatic tree pruning, surrogate splitter for missing data, visual display of the tree, acceptance of text data as well as numeric data, data transformation language (DTL) etc [5].

Alzheimer's and Breast cancer datasets were for the study. Alzheimer's disease is a progressive neurologic disorder that causes the brain to shrink (atrophy) and brain cells to die. Alzheimer's disease is the most common cause of dementia — a continuous decline in thinking, behavioural and social skills that affects a person's ability to function independently. The exact causes of Alzheimer's disease aren't fully understood. But at a basic level, brain proteins fail to function normally, which disrupts the work of brain cells (neurons) and triggers a series of toxic events. Neurons are damaged, lose connections to each other and eventually destroy memory and other important mental functions. Memory loss and confusion are the main symptoms. No exists, but medication and management strategies may temporarily improve symptoms [4], [9]

Breast cancer is the most common cancer diagnosed in women, accounting for more than 1 in 10 new cancer diagnoses each year. It is the second most common cause of death from cancer among women in the world. Breast cancer evolves silently, and most disease is discovered on routine screening. Breast cancer has now overtaken lung cancer as the world’s most commonly diagnosed cancer, according to statistics released by the International Agency for Research on Cancer (IARC) in December 2020. Identifying factors associated with an increased incidence of breast cancer development is important in general health screening for women [5], [10].

Predictive analytics automatically analyze databases using algorithms like single tree, decision tree, tree boost, support vector machine and neural network [3], [4], [7]-[9], [11]-[15].

The present study aims to analyze the datasets of selected diseases such as Alzheimer’s and Breast cancer which is affecting a majority of population using the DTREG data mining tool to understand the algorithm which works best and the important factors to be studied for predicting these diseases. Thereby helping in the early prognosis and diagnosis of diseases like Alzheimer’s and breast cancer.

METHODOLOGY

Two different diseases were selected for the study namely Alzheimer's and Breast cancer. Data mining tool used was DTREG. DTREG is a powerful application that can be easily installed on any Windows system. DTREG reads comma-separated value (CSV) data files that can be easily created from almost any data source. After creating the data file, just insert it into DTREG and DTREG complete all the work of creating decision trees, support vector machines, KMeans clustering, linear discriminant functions, linear regression or logistic regression models. Even complex analysis can be completed in minutes. DTREG can build classification trees and regression trees where the target variables are continuous, such as revenue or sales. The datasets chosen for the study were secondary data downloaded from Kaggle website, which is world's largest data science community with powerful tools and resources. This tool can be downloaded from the website www.dtreg.com. After installation of the tool, which is self-guided, the procedure to use the tool is explained below.

ProcedureA sample model was created by clicking on add project. Then the existing dataset was opened. On the project page details about the project were entered, i.e., title of project, input data file, data sub setting, character used to separate decimal point in input data file and character used to separate columns, notes about this project, etc. Then time series analysis was performed and the type of model to build was decided. Information about the variables was specified. The file was then saved. The file was then opened and Run analysis performed. A new report was displayed. The generated decision tree was viewed and the results interpreted.

RESULTS OF DATASETS USING DTREG

The parameters used in this Alzheimer's datasets were age, gender, socioeconomic status (SES), mini mental status examination (MMES), clinical dementia rating (CDR), estimated total intra cranial blood volume (eTIV), normalize whole brain volume (NWBV), atlas scaling factor (ASF) and the parameters used in breast cancer dataset include clump thickness, uniformity of cell size, uniformity of cell shape, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli and mitoses

Building a Model

There are five prediction models that were developed using classification technique and there were certain commonalities among all the models. All the models considered only 09 predictor variables and 01 target variable i.e., 'Group' for Alzheimer's and 'class' for Breast Cancer. The classification technique was used for analysis and the category weights were distributed over entire data file. The misclassification costs were equal (unitary) and the variableweights were also equal.

1. Single tree Model: Maximum splitting levels of single tree model is 10. Minimum size node to split is 10, whereas the minimum rows allowed in a node were 05. Maximum categories for continuous predictors were 1,000. Cross-validation method with ten folds was used for tree pruning and validation.

Model size for Alzheimer's - Maximum depth of the tree was 08. Total number of group splits was 27. The full tree has 15 terminal nodes. Minimum validation relative error occurred with 13 nodes. The relative error value was 0.2080 with a standard error of 0.0206 and the tree was pruned from 15 to 13 nodes.

Model size for Breast Cancer - The maximum depth of the tree was 08. Total number of group splits was 17. The full tree had 09 terminal nodes. The minimum validation relative error occurred with 08 nodes.

2. Decision tree Model: Maximum trees in Decision Tree Forest were 200. Maximum splitting levels was 50. Misclassification costs: equal (unitary). Minimum size node to split was 02 and maximum categories for continuous predictors were 100 for Alzheimer's and 1000 for Breast Cancer. Tree validation method was Out of Bag (OOB).

Model size for Alzheimer's - The full forest had 200 trees.
Three predictors (out of 09) were used for each split.
Maximum depth of any tree in the forest was 15 and average number of group splits in each tree was 43.6.Model size for Breast Cancer - Three predictors (out of 09) were used for each split. Maximum depth of any tree in the forest was 15. Average number of group splits in each tree was 27.4Tree boost Model: Maximum trees in Tree Boost series were 400. Maximum splitting levels were 05. Minimum size node to split was 10. Maximum categories for continuous predictors were 1,000. Random sampling (20%) validation method was used. Tree pruning criterion was the minimum absolute error.

Model size for Alzheimer's - All 09 predictors were considered for each split. Maximum depth of any tree in the series was 05. Average number of group splits in each tree was 28.6. The minimum error with the training data and the test data occurred with 391 trees. Hence the tree series was pruned to 391. \

Model size for Breast Cancer – In gradient tree boost model, all 09 predictors were considered for each split. Maximum depth of any tree in the series is 05. Average number of group splits in each tree was 9.4. The minimum error with the training data and the test data occurred with 311 trees and 104 trees respectively. Hence the tree series was pruned to 104 series.

3. Support Vector Machine Model: The type of SVM model was C-SVM and the SVM kernel function was radial basis function. SVM grid and pattern searches found optimal values for the following parameters. The search criterion was to minimize total error.For Alzheimer's dataset, the total number of points evaluated during search was 139 and the minimum error found by search was 0.069705. (ε = 0.001, C = 29.7019381, γ= 5.74349177). The number of support vectors used by the model was 193.

For Breast Cancer dataset, the total number of points evaluated during search was 148 and the minimum error found by search was 0.027818. (ε = 0.001, C = 0.1, γ= 0.001). The number of support vectors used by the model was 478.

4. Neural Network Model: Confusion matrix of Alzheimer's and Breast Cancer is shown in Figure 1 and 2. Neural network technique in Alzheimer's dataset was 478. 4. Neural Network Model: Confusion matrix of Alzheimer's and Breast Cancer is shown in Figure 1 and 2. Neural network technique in Alzheimer's dataset was used to predict whether the subject was converted, demented and non demented shown in Table I, II, III, IV. The probability values of occurrence of nondemented was found to be 0.5093834, demented was found to be 0.3914209 and the converted was found to be 0.0991957.Neural network technique in Breast Cancer dataset was used to predict whether the subject belonged to class 2 or class 4 is given in Table V, VI. The probability values of occurrence of class 2 was found to be 0.6500732 and the class 4 was found to be 0.3499268.

```
============  Confusion Matrix  ============

        --------  Training Data  --------

  Actual   : ---------Predicted Category--------
 Category  :  Converted    Demented  Nondemented
-----------: ----------- ----------- -----------
 Converted:       23           1           5
  Demented:        0         117           0
Nondemented:       0           0         152

       --------  Validation Data  --------

  Actual   : ---------Predicted Category--------
 Category  :  Converted    Demented  Nondemented
-----------: ----------- ----------- -----------
 Converted:        2           4           2
  Demented:        0          29           0
Nondemented:       0           0          38
```

Fig. 1. Confusion Matrix of Alzheimer's Disease.

```
--------  Training Data  --------

  Actual : ----Predicted Category---
 Category:        2          4
  --------:  ----------- -----------
        2:      348          7
        4:        3        188

--------  Validation Data  --------

  Actual : ----Predicted Category---
 Category:        2          4
  --------:  ----------- -----------
        2:       87          2
        4:        2         46
```

Fig. 2. Confusion Matrix of Breast Cancer

Table 1. Results for Converted Group of Alzheimer's Disease

	Single Tree Model		Decision Tree Model		Tree Boost Model		Support Vector Machine Model		Neural Network Model	
	Training data	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*
Total Records	373	373	373	373	298	75	373	373	373	373
Accuracy	93.57%	89.54%	91.69%	91.69%	97.99%	92.00%	99.73%	93.03%	100%	96.25%
Misclassi fication	93.03%	89.01%	91.15%	91.15%	97.99%	92.00%	99.73%	93.03%	100%	94.91%

Sensitivity	48.65%	24.32%	21.69%	21.62%	79.31%	25.00%	97.30%	45.95%	100%	75.68%
Specificity	98.51%	96.73%	99.40%	99.40%	100%	100%	100%	98.51%	100%	98.51%
Precision	78.26%	45.00%	80.00%	80.00%	100%	100%	100%	77.27%	100%	84.85%
Recall	48.65%	24.32%	21.62%	21.62%	79.31%	25.00%	97.30%	45.95%	100%	75.68%
Fmeasure	0.6000	0.3158	0.3404	0.3404	0.8846	0.4000	0.9863	0.5763	1.0000	0.8000

Table 2 Results For Demented Group of Alzheimer's Disease

	Single Tree Model		Decision Tree Model		Tree Boost Model		Support Vector Machine Model		Neural Network Model	
	Training data	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*
Total Records	373	373	373	373	298	75	373	373	373	373
Accuracy	95.71%	95.71%	95.71%	95.71%	99.66%	94.67%	100.00%	96.25%	100%	97.32%
Misclassi fication	93.03%	89.01%	91.15%	91.15%	97.99%	92.00%	99.73%	93.03%	100%	94.91%
Sensitivity	99.32%	99.32%	99.32%	99.32%	100.00%	100.00%	100.00%	97.95%	100%	95.21%
Specificity	93.39%	93.39%	93.39%	93.39%	99.45%	91.36%	100%	95.15%	100%	98.68%
Precision	90.63%	90.63%	90.63%	90.63%	99.15%	87.88%	100%	92.86%	100%	97.89%
Recall	98.63%	94.52%	99.32%	99.32%	100.00%	100.00%	100.00%	97.95%	95.21%	95.21%
Fmeasure	0.9505	0.9200	0.9477	0.9477	0.9957	0.9355	1.0000	0.9533	0.9653	0.9653

Table. 3 Results For Nondemented Group of Alzheimer's Disease

	Single Tree Model		Decision Tree Model		Tree Boost Model		Support Vector Machine Model		Neural Network Model	
	Training data	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*
Total Records	373	373	373	373	298	75	373	373	373	373
Accuracy	94.91%	94.91%	94.91%	94.91%	98.32%	97.33%	99.73%	96.51%	100%	96.25%
Misclassi fication	99.03%	89.01%	91.15%	91.15%	97.99%	92.00%	99.73%	93.03%	100%	94.91%
Sensitivity	98.42%	98.42%	98.42%	98.42%	100.00%	100.00%	100.00%	98.42%	100%	98.42%
Specificity	91.26%	91.26%	91.26%	91.26%	96.58%	94.59%	99.45%	94.54%	100%	93.99%
Precision	92.12%	92.12%	92.12%	92.12%	96.82%	95.00%	99.48%	94.92%	100%	94.42%
Recall	97.37%	97.37%	98.42%	98.42%	100.00%	100.00%	100.00%	98.42%	100%	98.42%
Fmeasure	0.9661	0.9512	0.9517	0.9517	0.9838	0.9744	0.9744	0.9664	1.0000	0.9639

Table 4. Lift and Gain of Alzheimer's Disease

Models	**Training Data**			**Validation data**		
	Converted	***Demented***	***Nondemented***	***Converted***	***Demented***	***Nondemented***
Single Tree	9.92%	39.14%	50.94%	9.92%	39.14%	50.94%
Decision Tree	9.92%	39.14%	50.94%	9.92%	39.14%	50.94%
Tree Boost	9.73%	39.26%	51.01%	10.67%	38.67%	50.67%
SVM	9.92%	39.14%	50.94%	9.92%	39.14%	50.94%
NN	9.92%	39.14%	50.94%	9.92%	39.14%	50.94%

Table 5. Results for Class 2 and Class 4 of Breast Cancer

	Single Tree Model		Decision Tree Model		Tree Boost Model		Support Vector Machine Model		Neural Network Model	
	Training data	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*	*Training data*	*Validation data*
Total Records	683	683	683	683	546	137	683	683	683	683
Accuracy	97.07%	95.75%	97.36%	97.36%	98.17%	97.08%	97.22%	97.22%	100%	98.10%
Misclassification	97.07%	95.75%	97.36%	97.36%	98.17%	97.08%	97.22%	97.22%	100%	98.01%
Sensitivity	97.91%	93.72%	98.33%	98.33%	98.43%	95.83%	97.49%	97.91%	100%	97.91%
Specificity	96.62%	96.85%	96.85%	96.85%	98.03%	97.75%	97.07%	96.85%	100%	98.20%
Precision	93.98%	94.12%	94.38%	94.38%	96.41%	95.83%	94.49%	94.35%	100%	96.69%
Recall	97.91%	93.72%	98.33%	98.33%	98.43%	95.83%	97.49%	97.91%	100%	97.91%
Fmeasure	0.9590	0.9392	0.9631	0.9631	0.9741	0.9583	0.9608	0.9610	1.0000	0.9730
Probability error	0.0000	0.017731	0.013951	0.013951	0.163465	0.033374	0.023082	0.024865	0.000364	0.01693
AUROC	0.982689	0.968370	0.993012	0.993012	0.999189	0.986891	0.995373	0.995043	1.0000	0.993696

Table 6. Lift and Gain of Breast Cancer

Models	Training Data		Validation data	
	Class 2	*Class 4*	*Class 2*	*Class 4*
Single Tree	65.01%	34.99%	65.01%	34.99%
Decision Tree	65.01%	34.99%	65.01%	34.99%
Tree Boost	34.85%	35.98%	65.96%	35.04%
SVM	65.01%	34.99%	65.01%	34.99%
NN	65.01%	34.99%	65.01%	34.99%

Importance of Variable for Alzheimer's: The variable 'Clinical Dementia Rating (CDR)'and 'estimated total intra cranial blood volume(eTIV)' was the most important variable according to all the models. However, the variable 'Normalize whole brain volume(nWBU)' was the second important variable as per Decision Tree Forest model. However, the variable 'Age' was the next important variable as per the Tree Boost model.

Importance of Variable for Breast Cancer: It could be concluded from the study that the variable 'Uniformity of cell size' and 'uniformity of cell shape' was the most important variable. However, the variable 'Bare Nucleoli' was the next important variable as per Decision Tree Forest model, and the Tree Boost model.

CONCLUSION

The main purpose of the research work was to analyze the datasets of selected diseases (Alzheimer's and Breast cancer) using the data mining software DTREG. All the models built for predicting the category of Alzheimer's patients and the survivability of breast cancer patients showed similar results and performance. However, the Neural network model is marginally better than the others as all 09 predictors were considered for each spit. The experimental result of accuracy, sensitivity, area under ROC curve and lift-gain were also slightly better in the Neural network model. Thus, the Neural network model was effective and the best model for predicting Alzheimer's and the survivability of breast cancer. The significant predictors for Alzheimer's were total intracranial blood volume, clinical dementia rating and age and for breast cancer, uniformity of cell size, cell shape and clump thickness were significant.

Data mining and machine learning can thus be of very good help in deciding the line of treatment to be followed by extracting knowledge from such suitable databases. The study carried out is generally a clinical decision support system. In this study, predictions have been made for diagnosis and treatment. It helps decision makers with recommendations by using clinical data stack and patient-specific data especially created by internal medicine specialists. In the study, a comparison has been made between different algorithms that could be used for the component of inference mechanism which is the brain of the clinical decision support systems. Also, the important predictors have been identified. Many more datasets could be added to improve the prediction accuracy. Further, a greater number of diseases and the availability of more data mining tools could be explored.

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A Systematic Review of Current Advances in Ischemic Stroke Detection and Segmentation

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A B S T R A C T

Ischemic stroke is now one of the vital factors for disability and mortality that globally affects millions of individuals each year inaccordance with the World Health Organization (WHO) contrast to hemorrhagic stroke. Treatment for an ischemic stroke as soon aspossible can assist to limit prolonged damage and even decreases the risk of mortality. The diagnosis is based on a neurologist's visualobservation, which may differ from one to another. On the other hand, Manual segmentation is a tedious and instinctive procedure that hasa conspicuous impact on Acute ischemic stroke encountered patient's prognosis. Numerous automated computer Aided Diagnosis (CAD)systems dependent on many statistical learning algorithms of machine learning (ML) and multi-neural network architecture of deep (DL) were considered to reduce the complexity of prediction and lesion segmentation in ischemic stroke and also lower the time required forthe manual procedure. This paper contemplates the Imaging modalities, Pre-processing techniques, and segmentation algorithms ofischemic stroke, as well as their performance based on comparing different evaluation parameters and their disadvantages. It highlights thecurrent needs, preferred modality, and possible research ideas in the stroke sector.

KeywordsBrain MRI, Deep Learning, Ischemia, Machine Learning, Pre-Processing.

1. INTRODUCTION

Cerebrovascular accidents (CVA), popularly known as stroke, are a group of brain disorders caused bycerebrovascular diseases (CVDs), like cerebral ischemia,intracerebral hemorrhage, and interventricular hemorrhage.Stroke is the world's second leading cause of disability anddeath. Every year, there are expected to be 15 million newCerebrovascular accident cases and a probability of 5 milliondeaths[1]. Ischemic stroke and hemorrhagic stroke are thetwo important types ofstrokes, which accounts for 87 percentand 13 percent of all Cerebrovascular Accidents respectively[2]. This review assessment makes the followingcontributions: (i) A complete summary of the variousischemic neuroimaging multi-modalities, their properties,and requirements. We examine the most well-known onesamong other modalities and make comments on theirapplicability, accessibility, and feasibility. (ii) Anencompassing overview of a variety of new strategies forstroke classification, identification, and lesion segmentation,organized by methods employed, datasets.

Ischemic Stroke

Ischemic stroke is engendered by thromboembolism that blocks or seals the brain, retina, and spinal cord bloodvessels. Figure 1 Staging the illustration of ischemic stroke.Large artery atherosclerosis, atrial fibrillation, and heartdisorders are significant origins of embolism.Small vessel dysfunction, which is linked to hypertensionand diabetes mellitus is another source of ischemic stroke[3],

[4]. Patients who encountered ischemic stroke must be treated adequately within 3-4.5 hours after the emergence of symptoms[5].

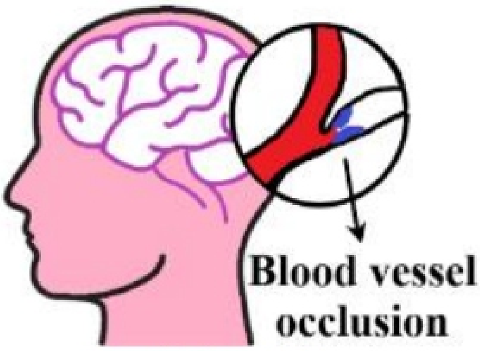

Figure 1. Ischemic stroke

Ischemic Stroke Imaging

The cerebral hemodynamics of ischemic stroke is represented by multimodal Computed Tomography (CT) andMagnetic resonance imaging (MRI), which are exploited tomake treatment decisions and also predict expectedoutcomes[6]. Table 1 Interprets the multimodal imagingtechniques used for acute ischemic stroke Computed Tomography combines advanced computertechnology with specialized x-ray equipment to generatemultiple medical images in any inside part of the body, whichincludes fat, muscles, bones, internal organs, and blood
vessels.

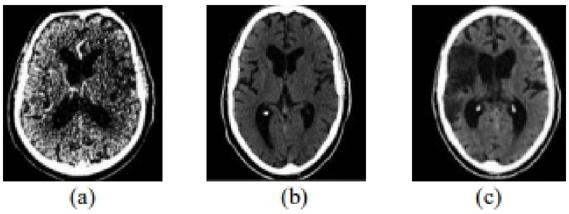

Figure 2. (a) Computed Angiography-Source Image (CTA-SI); (b) Non-Contrast CT (NCCT); (c) Ischemia on CTA-SI compared to NCCT

Non-contrasted Computed Tomography (NCCT),Computed Tomography Venography (CTV), ComputedTomography Angiography (CTA), and ComputedTomography Perfusion (CTP) are some of the CT imagingmodalities used to diagnose a stroke caused by blood clots orbleeding inside the brain. Figure 2 shows the improvedconspicuousness of ischemia on Computed TomographyAngiography source images (CTA-SI) compared toNon-contrasted Computed Tomography (NCCT).

Even though Computed Tomography is the mostcommonly available and fastest imaging modality, severalcomprehensive stroke centers prefer simplified MRI imagingover CT for two viable reasons.

Firstly, Magnetic resonanceimaging (MRI) is significantly more sensitive for detectingischemic stroke and more precise for determining the corevolume of infarction. Secondly, Magnetic ResonanceImaging (MRI) has less radiation dose and beam hardeningartifacts are absent when compared to ComputedTomography (CT)[7]–[10].

Magnetic resonance imaging (MRI) sequences used for ischemic stroke detection includes functional MRI (fMRI),T1-Weighted Magnetic resonance Imaging, T2-WeightedMagnetic Resonance Imaging, Diffusion-Weighted MagneticResonance Imaging (DWI), Fluid-Attenuated InversionRecovery (FLAIR) MRI and Gradient Record MagneticResonance Imaging (GRE)[11]–[16]. Figure 3 shows theaxial view of a normal brain's Magnetic Resonance Imaging(MRI) sequences. When compared to various imagingtechniques especially Computed Tomography (CT),Diffusion Weighted Imaging was more efficient in detectingacute ischemic stroke and more sensitive for finding morethan 33% of Middle Cerebral Artery involvement. DiffusionWeighted Imaging (DWI) measurements of lesion size, aswell as Apparent Diffusion Coefficient (ADC) values, arepossible indicators of clinical outcomes in ischemic stroke patients[17], [18].

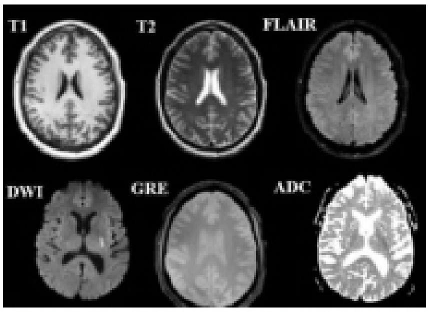

Figure 3. MRI sequences of normal brain

Table 1. Description of multimodal imaging for ischemic stroke detection

Imaging Modalities	Description
NCCT	NCCT generates soft tissue and bone images
CTA	CTA is applied to find thrombus as well as helps for intra-arterial thrombolysis
CTP	CTP is used to identify the parts of the brain that are sufficiently perfused with blood
T1w MRI	T1 imaging characterizes the brain tissue by smaller relaxation time based on the excitation state of protons in the water nucleus of the tissue a. Cerebrospinal fluid and inflammation appear dark b. Light white matter appearance c. Gray cortex appearance

T2w MRI	T2 imaging characterizes the brain tissue by a larger relaxation time based on the excitation state of protons in the water nucleus of the tissue a. Cerebrospinal fluid and inflammation appear bright b. Dark gray white matter appearance c. Light gray cortex appearance
FLAIR-MRI	It has a huge relaxation time than T2 weighted imaging to characterize tissue a. Dark Cerebrospinal Fluid appearance b. Dark gray white appearance c. Bright inflammation appearance d. Light gray cortex appearance
DWI-MRI	Recognize the random motions of water protons. It's a highly sensitive way of detecting strokes. The ADC (Apparent Diffusion Coefficient) quantifies the amount of water-molecule diffusion in the tissue.

Hemorrhagic stroke

Hemorrhagic strokes take place when an artery all of a sudden start bleeding inside the brain. As a consequence, thesegment of the body which is controlled by the injuredportion of the brain is unable to function properly.Intracranial hemorrhage (ICH) and subarachnoid hemorrhage(SAH) are the two types of hemorrhagic strokes[19], [20].Figure 4 shows the illustration of hemorrhagic stroke. BothComputed Tomography (CT) and Magnetic ResonanceImaging (MRI) are utilized for detecting Hemorrhagicstroke[21].

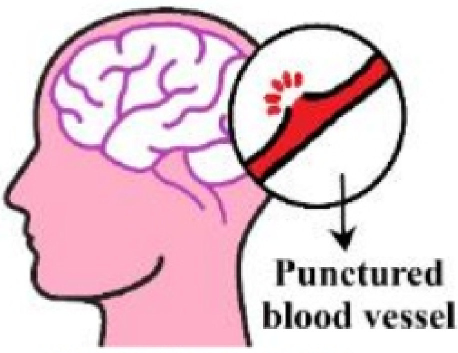

Figure 4. Hemorrhagic stroke

DATAACQUISITION

In general, the accuracy of ischemic stroke detection algorithms is intimately linked to the data sets to which theywere applied. As a result, the creation of a publicly accessiblebenchmarking system, such as Ischemic Stroke LesionSegmentation (ISLES): SISS and SPES, ENIGMA- strokerecovery: ATLAS lesion datasets, InteruniversityConsortium for Political and Social Research (ICPSR):stroke datasets, Neuroimaging Tools and ResourcesCollaboratory (NITRC): Autism Brain Imaging DataExchange (ABIDE), is used to ease the examination ofcurrent trending ML and DL application [22], [23].

Compared to other open-source datasets of ischemic stroke ISLES intends to provide a forum for comparing multiplesegmentation for ischemia lesion segmentation frommultispectral Magnetic Resonance Imaging (MRI) data fairlyand directly. For the following two tasks below, a commondataset of various ischemic stroke instances will be madeaccessible, as well as an appropriate automatic evaluationprocedure: Sub Acute Ischemic Stroke Detection (SISS) andStroke Perfusion (Penumbra) Estimation (SPES[24]). Table 2shows the data partitioning, number of centers, and numberof expert segment details of each SISS and SPES case in the2015 ISLES challenge.

Uncompressed Neuroimaging Informatics Technology Initiative (NIFTI) image data formats will be applied forSISS and SPES images. Partitioning the datasets into trainingand testing data that contains single focal and multifocalcases and also small lesion and large lesion cases. The datalayout of SISS and SPES of each case comes with itsrespective own folder which contains different types ofMagnetic Resonance Imaging (MRI) sequences.

Table 2. Dataset details of SISS and SPES

Data Types	Number of cases	Number of medical centers	Number of experts
SISS	28 Training 36 Testing	1 for Training 2 for Testing	1 Training 2 Testing
SPES	30 Training 20 Testing	1 for Training and Testing	1 Training and Testing

MRI sequences for SISS data are Fluid-Attenuated Inversion Recovery Magnetic Resonance Imaging (FLAIR),T2-Weighted Magnetic Resonance Imaging(T2-MRI) TurboSpin Echo (TSE) which rephases the pulse sequences,T1-Weighted Magnetic Resonance Imaging(T1-MRI)TSE/Turbo Field echo (TFE) that rephases the gradient echopulse sequences for contrast enhancement,Diffusion-Weighted Magnetic Resonance Imaging(DWI)[25], [26].

PRE-PROCESSING TECHNIQUES

To remove undesired artifacts and convert the data into the graded format, Magnetic Resonance Imaging (MRI) datamust be pre-processed. The most predominant pre-processingtechnique in stroke images isimage scaling also referred to asimage resizing or image intensity scaling. Incrementing ordecrementing the pixel values of rows and columns of animage is the working function of image intensity scaling. Ithelps to overcome the difficulties faced in the scrutiny of MRI [27].

The RGB format of the input images generated from medical imaging increases the computation time, memorysize, and coding difficulty, to avoid such difficulties graylevel conversion was introduced. It consists of two graylevels: 0 For black and 1 for white, it converts the RGB (Red,Green, Blue) image into a gray level image[28]. Skullstripping is one of the important Medical imagingpre-processing procedures that distinguish the brain tissuesfrom other region tissues like the skull and non-brainarea[29]–[31] in Magnetic Resonance Imaging (MRI) of thebrain for stroke followed by the Bias field correctionprocedure that is exclusively used to solve the problemcreated by the presence of low-frequency field which blursimage componentslike contours, edges, and pixel intensity inbrain Magnetic Resonance Imaging (MRI) images[32]. Toannihilate noise from MRI images, many filtering methodsare utilized, including the mean filter, median filter, adaptivemedian filter, weighted median filter, wiener filter, and soon[33]. To make ischemia region segmentation easier imageregistration was instigated to correlate two or more images indistinct MRI multimodalities it also differentiates the variations and identifies the anomalies manifested in theimages then helps to convey esteemed data in more than asingle MRI modality[34].

ROLE OF ARTIFICIAL INTELLIGENCE IN STROKEDETECTION AND LESION SEGMENTATION

Artificial intelligence (AI) is divergent from computer science and endeavors to replicate human intelligence tosolve problems[35]. Machine learning (ML) is a type of AIthat makes intelligent choices based on what has been learnedfrom parsed input. Deep learning (DL) is a type of machinelearning that uses an ANN (Artificial Neural Network) togenerate intelligent decisions without using pre-setinputs[36]–[38].

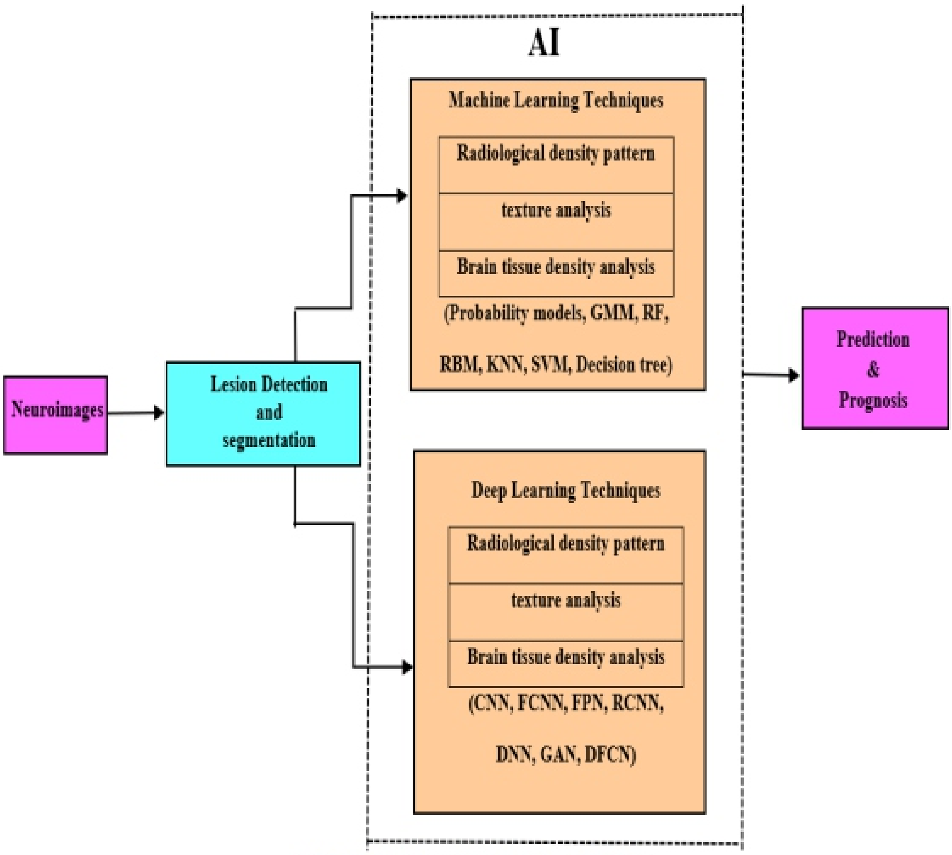

Figure 5. Role of AI in ischemic stroke

An ischemic stroke emerges on CT imaging as a dark attenuation patch that contrasts strongly with itssurroundings. Manually processing by a clinical specialisthas typically been the most successful for early diagnosis,although it consumes more time. As a result, machinelearning approaches are being used for automatic detection.Figure 5 shows the role of Artificial Intelligence in stroke management

Rajini et al. established a texture analysis as well asmidline shift tracing algorithm-based segmentation methodusing Machine learning where Cerebrospinal fluid (CSF)volume changed and acted as a cerebral edemabiomarker[39]. Guberina et al. used machine learning todetect early signs of infarction in the Alberta strokeprogram[40]. Lin et al. researched to evaluate the quality andpredict possible erroneous measurements triggered by ananomaly. Then examined and approved the density-baseddetection practicality. [41]. We see a lot of ML used with MRI since the feature extraction from it givesbetter results. In the instance of acute ischemic stroke,Teruyuki et al. discovered that a mismatch of anomaliesbetween perfusion–weighted Magnetic Resonance Imaging(MRI) and Diffusion Weighted Imaging (DWI) images couldaid in the identification of the penumbral region[42]. Maier etal. published a study comparing alternative machinelearning-based classification algorithms for lesionsegmentation[43]. In order to segment lesions, Mitra et al.researched the Bayesian–Markov random field (MRF)probabilistic technique and employed random forests (Rfs)to determine the location of lesion volumes[44]. Bharathi etal. investigated how handmade and unsupervised techniques,as well as derived features, may be used to improvesegmentation quality[45]. In order to help in the decision toadminister reperfusion therapy whenever stroke symptomsinitially emerged, Yoo et al. conducted research to determinethe ideal thresholds for Neuroimaging modality parameters[46]. Maier et al. suggested an effective algorithm forvoxelwise categorization based on additional tree forests,with a priority on reproducibility and noise resilience[47].Mark et al. used five machine learning techniques to identifyintense cerebral ischemia tissues that can recuperate afterreperfusion, including the generalized linear model, adaptiveboosting model, Support Vector Machine, additive model,and random forests[48]. To enhance probability maps, ChenH. et al. proposed RFs which make use of dense sparse fields[49]. To train Radial Basis Function (RBF) kernel SVMmodel and Artificial Neural Network (ANN), Karthik et al.used discrete curvelet transformation over various scales of features. Pereira et al. implemented a Restricted Boltzmann Machine (RBM) to learn lesion features [50]. Delaunaytriangulation (DT) was used by Subudhia et al. to optimizedelineation, and FODPSO was used to determine theparameters [51].

A new paradigm for stroke diagnosis has emerged as a result of the development of deep learning. A quicker andmore effective network for feature extraction was put forth byHu et al[52]. Islam et al. suggested an adaptivelearning-based training segmentation technique that wouldfind and regulate higher-order conflicts among ground–truthand mapped segments. The model is made up of a conceptive,which demonstrates the synthesized, and raciallydiscriminatory model, that calculates the probability ofsamples drawn from real-world data[53]. For voxel-wiseregion detection, Bertels et al. Designed an ConvolutionalNeural Network (CNN) architectural model using data froman adjacent voxel[54]. Dou et al. suggested a cascadeframework-based automated 3D CNN model for executing adetection operation[55]. To get higher image quality forprecision, Wang et al. developed a DWI synthesized usingperfusion maps[56]. To detect hyper-intense locations inFLAIR and T2w imaging, Li et al. proposed a Faster-CNN-based architecture[57]. Wielding a generativeadversarial network (GAN), Alex et al. devised asemi-supervised method for segmenting brain lesions[58]. Toeffectively segment the acute ischemic stroke location usingmulti-modality Imaging studies, Liu et al. suggested a DCCN(Res–CNN). Utilizing multimodality enhances segmentationperformance in comparison to the single modality variant[59]. For an accurate reconstruction, Karthik et al.presented a supervised Deep Fusion Clustering Network(DFCN) that employed an activation unit as ReLU in the lasttwo layers of the network[60].

CHALLENGES AND FUTURE ORIENTATIONS

Evaluation is very challenging for all Computed Aided Diagnosis approaches, implementations, and strategies wecame across while assessing the stroke area because theywere all based on different datasets. Although severaltechniques claimed to be entirely automated, theynevertheless required human input or contact for setting upparameters. A robust intelligent system would be necessaryfor a fully automated procedure that can adjust and alter inaccordance with the current state of the patient and theseverity of their symptoms. It would open up a number ofpossibilities in terms of the potential for artificialintelligence. We discovered lessresearch on the classificationof stroke subclasses and paucity on the effectual progressionof stroke lesion volume extraction across time. For betterstudy and a clearer understanding of their impact, a diversecollection including images from different datasets should bedeveloped

There are various possible directions for future research:(I) Artificial Intelligence-based automated system that greatlyenhances ischemic stroke early detection (ii) Creating a massive heterogeneous public database (iii) Developing Graphical User Interface (GUI) for acute ischemic stroke(AIS) detection and segmentation by utilizing effective MLand DL Approaches (iii)Designing a prototype to monitorstroke encountered patients using predictive AI-models onthis basis cloud.

CONCLUSION

In this systematic review, a distinct segmentation approach emphasizing infarct cores and penumbra estimation ofischemic stroke was presented. From brain images, theoffered algorithms could identify the existence of a strokelesion. It's difficult for academics to create a more reliablealgorithm because of the computation time and accuracyrequirements. The segmentation of the stroke lesions aloneachieves the accuracy of approximately 81% to 99.1%contemplated in above section 4. Additionally, the gapappears when all state-of-the-art approaches areinsufficiently applied in clinical settings. It may be possiblefor the medical and engineering fields to collaborate todevelop an accomplishing end-to-end automatic genericframework for recognizing stroke lesions.

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