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Contents

Improving the Predicting Rate of Alzheimer's Disease through Neuroimaging Data using Deep Learning Approaches

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A B S T R A C T

Recently deep learning has shown a improved performance than machine learning in many of the areas like pattern recognition, image classification computer vision, video segmentation and many more. But out of all these areas, disease classification is one of the major areain which deep learning has shown a remarkable performance than the traditional machine learning algorithms especially in the area ofimage recognition. Machine learning algorithms are not enough capable to handle the image so in this work we will apply the deep learningapproach on the Alzheimer's disease dataset for performing the early detection and classification of the disease and this has done throughusing neuroimaging data. Previous work done in this area was based on traditional machine learning algorithm and they have used stackedauto encoder (SAC) for dimensionality reduction and they have achieved a classification accuracy of 83.7% during the prediction frominitial symptom to final development of Alzheimer's disease. The deep learning algorithm ResNet which is implemented in this paper hasshown a classification accuracy of 93% and this is also achieved without applying any dimensionality reduction approach and this has beenconsidered as the best predictive rate on the neuroimaging data till now. The applied ResNet is the improved ResNet and the comparison ofboth the Resnet models are shown in this work. This deep learning application will also be useful for other types of disease classification likecancer, diabetics, etc.

KeywordsADNI, Convolutions, Mild Cognitive Impairments (MCI), ReLU, Residual Block, ResNet.

INTRODUCTI

One of neuropsychologists' major problems in the last 50 years is the perception of the cognitive and behavioralsymptoms of dementia and the association between it andunderlying brain pathology. Due to increase in the age ofdementia-related neurodegenerative disorders, there has beensignificantly increased in the risk over the years. Althoughthe idea of dementia existed for several thousand years, themain clinical and related neurodegenerative diseases werenot discovered until the beginning of the past century. In1907 Alzheimer's Aloysius has analysed the symptomsduring the treatment of a 51 year old woman and hisdescription has become the first neuropsychologicalcharacterization of the disorder. Alzheimer's disease (AD),the most prevalent type of dementia, is a significant health concern in the

21st century and it is estimated 5.5 million people aged 65 and over live with AD. Lots of effort isalready done by many researchers for the early detection ofthe disease especially in the presymptomatic stages, in orderto delay or prevent the development of diseases [1].

It happens that Alzheimer disease memory get affected slowly, unresponsive, everyday living skills may degradeslowly, and unexpected changes in personality andcompliance may occur. Even they did not remember thefriends and their loved ones. The burden on themselves andtheir families is also great. The disease of Alzheimer is more of an irreversible and psychic blow. All treatments are limited to slow the degradation cycle and cause a rift between patients and their families.

The research discussed in [2] that person who is taking care of AD patient also suffers from higher depressionincidence. Early prediction, identification and identificationare necessary. Although this disease is irreversible, thedisease can be recognized early and we can takeenvironmental and drug intervention measures to slow thedisease progression. In this work we are incorporatingtechnology for the prediction of AD through deep learningapproaches but before discussing about the deep learningimplementation, this work will also focus some of theprevious work done in this area. Already there are someadvanced neuroimaging technology like MRI and PET whichare already doing good job in the area of identification ofstructural and molecular markers of AD [3]. Despite of allthese development in the area of neuro imaging there hasbeen rapid developments in neuroimaging techniques whichhave made incorporation of high-scale multimodalneuroimaging data a challenge.

Consequently, interest in computer-aided learning approaches for integrative analysis has rapidly increased.Some method are already developed for early detection andprediction of AD [4] which can be considered as well-knownpattern analysis methods, such as Linear Discriminantanalysis (LDA), logistic regression (LR), support vector machine (SVM), linear program boosting method (LPBM) and Support Vector Machine – Recursive Feature Elimination (SVM – RFE).

During the implementation of machine learning algorithms there are some predefine method on the basis of whichclassification has to be done [5]. The focus of machinelearning algorithm is mainly on four steps i.e. featureselection, feature extraction, dimensionality reduction andthe last one is the classification algorithm. Although the firstthree steps are considered to be preprocessing steps and allthese procedures requires specialized skills and optimizationtechniques. The problem with these preprocessing techniquesis that they require much amount of time during theoperations.

Other than the time consumption there are some more problems are there when dealing with machine learningclassification algorithm for the prediction of AD. One of theproblems occurs with the use of feature selection approach isthat during the selection of features from the variousneuroimaging modalities to inherit more informativemeasures based on combinations this may also involve thefactors like subcortical volumes, cortical thickness, graymatter densities, brain glucose, etc and this are considered tobe a problem [6].

To overcome from all these problems occur due to machine learning algorithms in the area of AD, deep learningalgorithm came into existence. The deep learning algorithmsare using the raw data from the neuroimaging for generatingthe essential features which has performed considerableattention during high dimensional medical image analysis.[7]In this work Convolutional Neural Network Algorithm isused for prediction purpose and it has outperformed otherstate of the art algorithm.

BACKGROUND STUDY

In this section discussion will be on research which has done earlier in the area of AD through machine learningapproaches on the different types of images generated by theneuroimaging devices. Lu et al. [8] has implemented a newdeep-learning framework for discriminating people with ADthrough the use of a deep neural multimodal and multiscalenetwork. This system has computed 82.4 percent specificityto classify individuals with mild cognitive impairment (MCI)that converts to AD at 3 years prior to conversion (86.4percent conversion accuracy within one- to three years), aclinically diagnosed sensitivity of 94.23% and aspecialization of 86.3 percent for non-demented controls Classification.

Ortiz et al. [9] has solved the detection problem through sparsely replicated data, which also allows the combinationof specialized classifiers for the classification of multimodalimages (PET and MRI). It's a new way of efficientlycombining SVC classifications which is, using the distancemeasured for each class in each classifier for the hyperplane,allowing the most discriminatory image mode to be selectedin each case. While functions in diagnosed Alzheimer's patients (AD) are clearly visible as compared to control subjects, behavioral changes that appears in the early stagesof the disease and are more significant in the case of patientswith Mild Cognitive Impairment (MCI).

Shi et al. [10] Has implemented a system that is used to fuse and learn task representation from MultimodalNeuroimaging Data to diagnose AD with a multimodalstacked DPN algorithm (MM-SDPN) consisting of two stepSDPN (MM-SDPN). Specifically, two SDPNs are first usedto learn high-level MRI and PET characteristics, which arethen given to another SDPN to combine multimodalneuroimaging information.

For binary and multi-class classification activities, the proposed MM-SDPN algorithmis used for the ADNI dataset. The result has shown thatmultimodal, learning-based AD diagnostic algorithms areperforming better than the other algorithms which are based on stacked encoder.

Raza et al. [11] has proposed a new machine learning algorithms which is used to diagnose and monitoring ofAD-like disease. The diagnosis phase of AD-like diseases isachieved by interpreting deep learning magnetic resonanceimaging (MRI) scans, and an active monitoring system isprovided to track the everyday behavior of subjects by usinginertial sensors used by their bodies. The activity trackingoffers a supportive structure for daily tasks and assesses thevulnerability of patients based on the level of activity. Incontrast to well-known current methods, this model hasshown 82% improvement over other existing model.

Frazer et al. [12] has derived the data are derived from the Dementia Bank corpus, which provides 240 narrativesamples to 167 patients diagnosed with "possible" or"probable" AD, and an additional 233 to 97 controls. In orderto differentiate between AD-participants and successfulchecks they measured a number of linguistic variables fromtranscripts and acoustic variables through the correspondingaudio files. They pursue an exploratory factors study on thesespeech and language interventions with an oblique promaxrotation to analyze the degree of heterogeneity of ADlinguistic impairments and provide the interpretation of theresulting factors.

Ahmad et al. [13] implemented a novel method for fusing existing color spaces which has shown more effective resultsin practice than single color spaces. The segmented objectsare the mouths, ears, paws, legs, and leaves of the tree. Usingmultiple databases to reflect these issues, the ANN wastrained as an object or non-object to the color of the pixel andits surrounding 8 neighbors. In the testing phase, the traineddata was utilized to split the nine pixels of the text image intoan object or non-object. To analyze the impacts of theblending done on different types of color information fromthe various color models of the targeted pixel they have used the vector function for training the model.

PROPOSED METHODOLOGY

I. Dataset

In this work we have obtained data from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database [14]. Thepatients are selected on the basis of three categories i.e.normal controls (NC), mild cognitive impairments (MCI) andAlzheimer's disease. A total of 8809 data samples areavailable and for each patient both MRI images and clinicaldata was captured. To perform the research we have takenstructural T1-weighted Magnetic Resonance Imaging (MRI),because it is easily available with all the patients. Although the images retrieved from the ADNI database are alreadypreprocessed through different pipeline stages. To extract theimage of the brain, an ANTs Cortical Thickness Pipeline wasexecuted. After this execution an affine transform was applied on all the brain images so that they have the same orientation.

ii. ResNet

In this work the implementation of deep learning will be done in the form of Convolutional Neural Network (CNN)[15] by implementing the ResNet3D or conv residualnetwork. We have used ResNet3D because these neuralnetworks are getting deeper and deeper. Before discussingResNet3D, first we will discuss about the basic concept ofResNet.

The ResNet neural network trained a very deep 152-layer neural network that has some very interesting tricks and ideaswhich can effectively work on the image recognition system.By using ResNet we can build effective ConvolutionalNeural Network. Although it's very difficult to train deepneural networks because of vanishing and exploding gradienttypes of problems. In this network, activation from one layerand suddenly feed it to another layer even much deeper in theneural network. Through this we can build ResNet whichenables you to train very, very deep networks, sometimeseven networks of over 100 layers. The given below equation will show how the residual block will be build for ResNets.:

In the initial processing of neural network assume the two layers in the network with some activations in x[l] layer, thengo to x[l+1], and then activation after two layers is x[l+2].Now let's see the computation of x[l] and then apply thelinearity into it which can be performed by using the equationgiven below:

$$z[l+1] = w[l+1]\, x[l] + b[l+1] \qquad (1)$$

In the above equation, the input is multiplied with the weight matrix and adds the bias vector. Later on to get x[l+1],a ReLU activation function is added for the nonlinearity [16].This is achieved by the equation:

$$x[l+1] = R(z[l+1]). \qquad (2)$$

R represents the ReLU activation function The same linear steps will be followed in the next layer,

$$z[l+2] = w[l+2]\, x[l+1] + b[l+2] \qquad (3)$$

At last there will be another ReLU operation that will be performed for the non linearity and this is represented by the equation:

$$x[l+2] = R(z[l+2]) \qquad (4)$$

Through the above equation it can be easily observe that to get information from x[l] to x[l+2], it needs to go through allthese steps and they are considered to be the main path of thisset of layers. We will make some changes in the residual netby putting x[l], and just forward it first, copy it and forward iton neural network by directly sending the information fromx[l] to x[l+2]. So rather than following a complete path theinformation from x[l] can now follow a direct path to gomuch deeper into the neural network. So the last equation will be

$$x[l+2] = R\ (z[l+2] + x[l]). \qquad (5)$$

The inclusion of x[l] will form this residual block. These pictures can be directly send to the top by creating adirect path to reach there. The nodes represented here areapplied with linearity function and ReLU because the skipconnection or the shortcut paths are applied before the nonlinearity and the captured image is passed through the secondlayer. After the linear transformation, x[l] is injected justbefore the ReLU and it jumps directly by skipping over alayer (almost 2 layer) in order to process the informationdeeper into the neural network. It can easily analysed thatresidual blocks allows to train much deeper neural networksand the way a ResNet is build by taking away many of theseresidual blocks, blocks like this and stacking them together toform a deep network. So, if the network is not residual, thenwe can build the residual net by adding all those skipconnections, even if they're short connections like this existin a model. In this network every two layers ends up with theadditional change that transforms each of them into a residualblock and the use of regular optimization algorithm, such as agradient descent, or one of the fancier optimizationalgorithms on a train or a simple network is done. So withoutall the extra residuals, without any extra short cuts or skipconnections, it has been analysed that the increase in thenumber of layers will tends to decrease the training error butafter a while they tend to go back up again.

In order to deepen the neural network, the performance has to be improved on the training set. But what happens toResNet is that even as the number of layers gets higher thetraining error also tends to increase even if we train a networkof over a hundred layers. There has been insertion of differenttypes of activations in the intermediate layers that helps toenter into the deeper neural network. Due to this during thetraining of deeper neural networks, the real loss ofperformance will get minimized with the help of vanishingand exploding the gradient problems.

To perform well on the training set, let us take X feeding in to some big neural network and just outputs some activationx[l]. Let's say for this example that you are going to modify the neural network to make it a little bit deeper. So, use the same big NN, and this output's x[l], and we're going to add a couple extra layers to this network so let's add one layer thereand another layer there. And just for output x[l+2]. Only let'smake this a ResNet block, a residual block with that extra short cut.

Given below figure shows the block diagram of ResNet

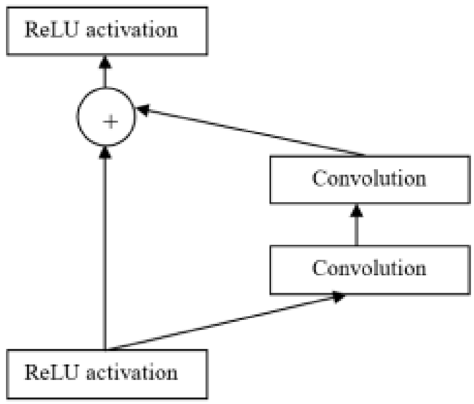

Figure 1. Block diagram of ResNet

Activation function ReLU [17] is defined by the equation:

$$f(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (6)$$

In the above equation f(x) is the output function and x is the input unit. It is easy to train CNN's because ReLU function alleviates the problems of vanishing gradients through its identity map in the positive quadrants.

Mathematically we can define convolution as function that derived by the integration of two different functions so that it can show how one has made impact on the another.

Convolution [18] is defined as:

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau \quad (7)$$

F and g are the two different function in this equation and they are integrated to form a convolution.

iii. Improving the ResNet

We use 6 residual blocks each for ResNet like architecture whose identity mapping comprises a minimum of twoconvolutions with batch normalization and ReLU of 3x3x3filter size and 64 or 128 filters. In improved ResNet,ConvBlocks are replaced by convolutionary layers from thestandard ResNet. The range is reduced by three 2x2x2 phaseconvolutions until residual blocks and a limit of one 5x5x5kernel pooling layer in front of full-connected layer. Just afterthe first fully connected layer, a dropout with p=0.7 and batchnormalization has been applied. Lastly there is a second fullyconnected layer with softmax function [19] to produce the output probabilities.

In figure 1 we have shown the flowchart of the proposed work, the flowchart has shown the various steps which isperformed during the classification of neuroimaging data.The data is processed through improved ResNet model and it has computed the different parameters like accuracy, AUC, sensitivity and specificity.

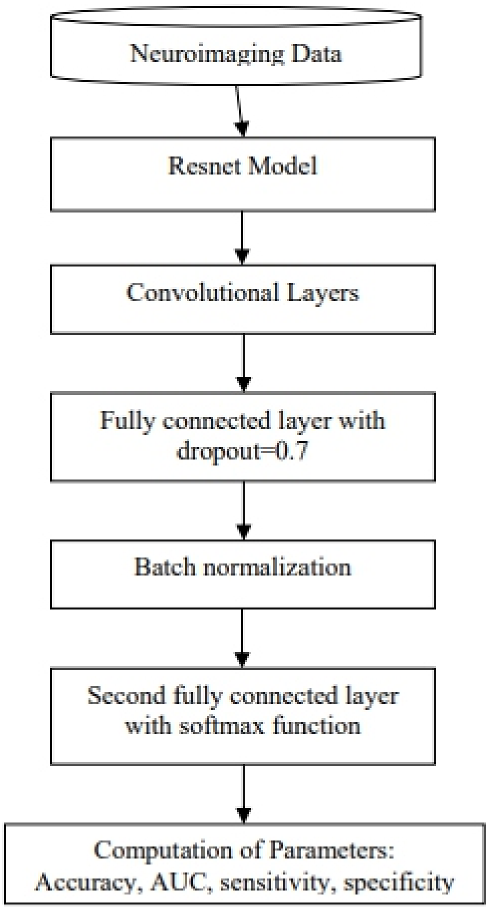

Figure 2. Flowchart of the proposed ResNet convolution Model.

EXPERIMENT AND RESULT ANALYSIS

The work is implemented using Python 3 and the data is based on neuroimaging data with the conversion predictor,we minimize a balanced class binary cross-entropy weightedloss function, with initial learning rate 10−3 using theNesterov momentum optimizer [20]. There will be adecrement of 10 fold after the epoch of 30 and 50. The batchsize is of 128 dimensions, the reason for selecting thisdimension is to match the entire batch into the GPU. Thereare 70 epochs in total.

Execution of 5-fold group cross-validation with five different folds is done to make the classification performancemore accurate. When there is different scan of the samepatient then we have use the patient id for training and testingpurpose. During the cross validation procedure of theneuroimaging data, we have trained a separate neuralnetwork on the training dataset and have used the validationset for managing the learning rate.

The metrics used for the computing the prediction performances of the model are the accuracy, AUC, sensitivityand specificity [21]. The classification implemented in thiswork is binary classification in which class 0 represents thestable MCI and class 1 represents the converged MCI [22].

The dataset is split in training and testing dataset of 75% and 25% of the dataset respectively.

RESULTS

Given below Table 1. will shows the result computed from the neuroimaging dataset with the implementation ofimproved ResNet Covolutional Neural Network. The resultsare compared with the other state of algorithms like logistic regression [23] and Xgboost [24].

Table 1. Comparison of the models on the basis of different types of metrics

Models	Accuracy	AUC	Sensitivity	Specificity
Logistic Regression (Clinical dataset)	77%	0.61	0.67	0.76
Xgboost (Clinical dataset)	76%	0.59	0.66	0.78
Inception-v4 [25]	75%	0.587	0.68	0.78
ResNet	82%	0.638	0.73	0.77
Improved ResNet	93%	0.671	0.94	0.93

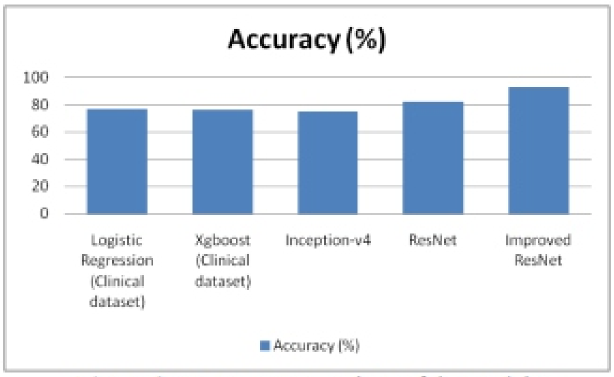

Figure 3. Accuracy comparison of the models

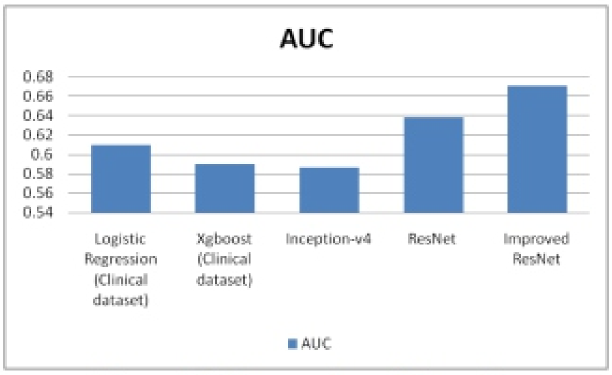

Figure 4. AUC comparison of the models

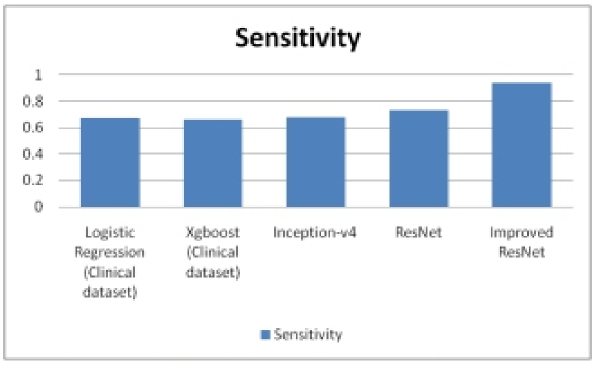

Figure 5. Sensitivity comparison of the models

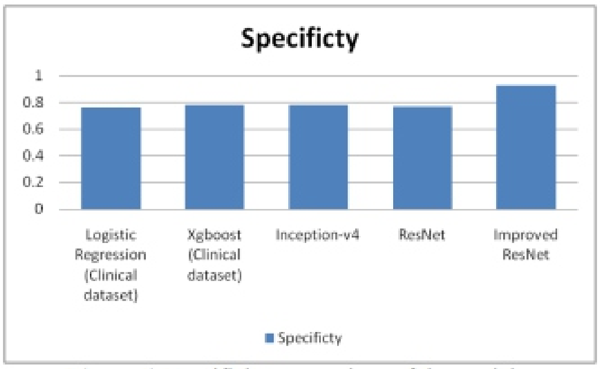

Figure 6. Specificity comparison of the models

Above graphs has shown the result analysis based on ADNI database computed by the improved ResNet model.The model has applied on the ADNI dataset and it hasachieved the accuracy of 93%, AUC of 0.671, sensitivity of0.94 and the value of specificity is 0.93. The model hasoutperform other model due to its improved results.

CONCLUSION

The discussed model in this work has achieved classification accuracy i.e. 93%, better than the other state ofthe art algorithms. Although from this work it has beenobserved that deep learning algorithms can handle thecomplex problems by applying the property of non linearityand this works fine especially in case of single classneuroimaging prediction. But still it is a challenge to providea good accuracy on the multi-class classification network andthis will be the future development in this area which can beapplied for diagnostic and prognosis biomarkers forpsychiatric and neurological disorders.

REFERENCES

[1] J. E. Galvin, "Prevention of Alzheimer's Disease: Lessons Learned and Applied," J. Am. Geriatr. Soc., 2017.

[2] A. S. Alfakhri et al., "Depression among caregivers of patients with dementia," Inq. (United States), 2018.

[3] D. P. Veitch et al., "Understanding disease progression and improving Alzheimer's disease clinical trials: Recent high lights from the Alzheimer's Disease Neuroimaging Initiative," Alzheimer's and Dementia. 2019.

[4] S. Rathore, M. Habes, M. A. Iftikhar, A. Shacklett, and C. Davatzikos, "A review on neuroimaging-based classification studies and associated feature extraction methods for Alzheimer's disease and its prodromal stages," NeuroImage. 2017.

[5] N. S. Vassilieva, "Content-based image retrieval methods," Program. Comput. Softw., 2009.

[6] B. C. Riedel et al., "Uncovering Biologically Coherent Peripheral Signatures of Health and Risk for Alzheimer's Disease in the Aging Brain," Front. Aging Neurosci., 2018.

[7] S. M. Plis et al., "Deep learning for neuroimaging: A validation study," Front. Neurosci., 2014.

[8] D. Lu et al., "Multimodal and Multiscale Deep Neural Networks for the Early Diagnosis of Alzheimer's Disease using structural MR and FDG-PET images," Sci. Rep., 2018.

[9] A. Ortiz, F. Lozano, J. M. Gorriz, J. Ramirez, and F. J. Martinez Murcia, "Discriminative Sparse Features for Alzheimer's Disease Diagnosis Using Multimodal Image Data," Curr. Alzheimer Res., 2017.

[10] J. Shi, X. Zheng, Y. Li, Q. Zhang, and S. Ying, "Multimodal Neuroimaging Feature Learning with

Neuroimaging Feature Learning with Multimodal Stacked Deep Polynomial Networks for Diagnosis of Alzheimer's Disease," IEEE J. Biomed. Heal. Informatics, 2018.

[11] M. Raza, M. Awais, W. Ellahi, N. Aslam, H. X. Nguyen, and H. Le-Minh, "Diagnosis and monitoring of Alzheimer's patients using classical and deep learning techniques," Expert Syst. Appl., 2019.

[12] K. C. Fraser, J. A. Meltzer, and F. Rudzicz, "Linguistic features identify Alzheimer's disease in narrative speech," J. Alzheimer's Dis., 2015.

[13] A. B. A. Hassanat, M. Alkasassbeh, M. Al-awadi, and E. A. A. Alhasanat, "Color-based object segmentation method using artificial neural network," Simul. Model. Pract. Theory, 2016.

[14] S. G. Mueller et al., "The Alzheimer's disease neuroimaging initiative," Neuroimaging Clinics of North America. 2005.

[15] Q. Zhang, M. Zhang, T. Chen, Z. Sun, Y. Ma, and B. Yu, "Recent advances in convolutional neural network acceleration," Neurocomputing, 2019.

[16] B. Hanin, "Universal Function Approximation by Deep Neural Nets with Bounded Width and ReLU Activations," Mathematics, 2019.

[17] R. Arora, A. Basu, P. Mianjy, and A. Mukherjee, "Understanding deep neural networks with rectified linear units," in 6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings, 2018.

[18] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in Proceedings - 30th Conference on Computer Vision and Pattern Recognition, CVPR 2017, 2017.

[19] M. D. Zeiler and R. Fergus, "Visualizing and Understanding Convolutional Networks arXiv:1311.2901v3 [cs.CV] 28 Nov 2013," Comput. Vision–ECCV 2014, vol. 8689, pp. 818–833, 2014.

[20] R. Singari, K. Singla, and G. Chawla, "Deep Learning Framework for Steel Surface Defects Classification," Int. J. Adv. Prod. Ind. Eng., 2019.

[21] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," Pattern Recognit., 1997.

[22] R. C. Petersen, "Mild cognitive impairment as a diagnostic entity," in Journal of Internal Medicine, 2004.

[23] D. Bzdok, M. Eickenberg, O. Grisel, B. Thirion, and G. Varoquaux, "Semi-supervised factored logistic regression for high-dimensional neuroimaging data," in Advances in Neural Information Processing Systems, 2015.

[24] C. Gao et al., "Model-based and model-free machine learning techniques for diagnostic prediction and classification of clinical outcomes in Parkinson's disease," Sci. Rep., 2018.

[25] C. Szegedy et al., "Inception v4," Popul. Health Manag., 2015

Comparison of the Effect of Boiled Cotton Swabs, Alcohol Swabs and without Swabbing on Skin Infection before an Injection

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A B S T R A C T

Skin infection is a type of infection that can be caused by bacteria, fungus, viruses or parasites. Nowadays, the world is going through a critical time which has affected the people in many ways and therefore, the people need to take care of their health and health-related problems to save the cost and time without compromising health. For the treatment of skin related infections, the medical professionals uses injections in order to make the patient comfortable and safe. Recommendations about the need to use alcohol before injection of the vaccine are contradictory and based on proof at low rates. Alcohol is used to disinfect the skin prior to injections in order to prevent infections caused by bacteria on the skin being injected within tissue. Alcohol has been shown to be good disinfectant, reducing the number of bacteria on skin by 47-91%. The preparation of skin of the patient before injection is generally done by washing the skin that is visibly soiled or dirty. Swabbing of the clean skin before giving an injection is unnecessary. If swabbing with an antiseptic is selected for use, use a clean, single-use swab and maintain product-specific recommended contact time.Therefore the idea of preparation for the injection site came into effect, but there are different recommendations for preparation of the skin before injection leaving nurses in confusion, and they took up the present analysis.

KeywordsAlcohol, Antiseptic, Disinfectant, Skin infection, Swabbing, Treatment, Vaccine.

INTRODUCTION

Various health authorities around the world have detailed recommendations outlining best methods for administering vaccines. For certain nations, for example Canada, this policy involves pre-injection washing of the skin with alcohol.Alcohol skin washing is a common practice resulting from the alcohol's proven efficacy in decreasing skin bacterial counts that has been extrapolated to suggest a lower risk of skin infections[1].Injections are the most common health care procedures performed by nurses at an average rate of 16 billion administrations each year, according to the World Health Organization (WHO) and the Safe Injection Global Network (SIGN).Over the course of childhood vaccine programs approximately 1 billion injections are issued annually[2].

It is believed that the skin is infected with organisms which, when injected into the body by injection needle, may cause pathological changes.Based on this premise, medical students are instructed to have skin prepared by trainee physicians, nurses and patients before injection by washing with some sort of antiseptic to avoid infection at the injection site[3].Since the 19th century, alcohol swab (saturated with 70 percent isopropyl) has been used to prepare the skin before surgery as a highly effective and oldest topical antiseptic.Alcohol destroys most of the vegetative bacteria, but has little effect on fungal spores according to Willium and his colleagues.Another research found that alcohol does not evaporate easily, and that some of it can be transferred to the body with the injection needle through the skin, giving rise to an uncomfortable stinging sensation when used[4].

The WHO (World Health Organisation) recommendation is based on a systematic analysis that finds no signs of infection when subcutaneous insulin injections have missed alcohol skin washing.No alcohol gain recorded from four additional studies including intramuscular, intradermal, and subcutaneous injections of a range of medications, including vaccines.In all research there are methodological limitations that prohibit definitive conclusions from being drawn, including lack of sufficient randomization or blinding, evaluation of skin reactions using non-validated instruments, retrospective data collection and passive recording of adverse events.Including, no study actually tested vaccine injections. In addition, Cook recently summarized 1,010 cases of cellulitis and 360 cases of infectious abscess after vaccination documented in passive surveillance systems, vaccine studies and published papers, and proposed additional randomized trials to investigate this problem[5]. The new health care system is profoundly involved in reducing unnecessary tests, therapies, and procedures, as exemplified by the American Board of Internal Medicine's (ABIM) Choosing Wisely campaign.

A comprehensive systematic review extensively analysed paediatric medical overuse behaviours and outlined the related costs and risks of harm to patients. Alcohol exclusion for skin washing can qualify as an unnecessary treatment because it has not been shown to have an effect on the risk of infection. There are possible advantages to eliminating alcohol swabs, including: 1) reduction to resource usage due to shorter processing time and supplies, 2) reduction of pre-procedural anxiety due to injection alcohol, and 3) reduction of pain due to alcohol monitoring in the tissue during injection[6].

It is supposed that the skin is expected to be infected with pathogens that may cause pathological changes when injected into the body by injection needle. This presumption leads to training medical students, trainee physicians, nurses, and patients to have pre-injection skin prepared by washing with some sort of antiseptic to avoid infection at the injection site.The alcohol swabs have been used from earlier times to sterilize the injection site prior to injection.

But then there was evidence that alcohol causes discomfort to the skin. Alcohol may also induce the inactivation of live vaccines. For these purposes, the practice of using boiled cotton swabs for immunization to clean up the injection site came into use. The use of boiled cotton swabs is the most common and preferred method for preparing the immunization site for injection[7].

In the Medical Officers' Immunization Handbook, Government of India, it is recommended that if the injection site is dirty then clean it with a clean water swab and administer the vaccine. Prior to administering injection, researchers from a few years have questioned the importance of skin preparation. A ground-breaking research carried out by Dann at a medical centre in which patients between 4 and 66 years of age received more than 5000 injections without skin preparation.No instances of infection have been reported, either systemic or local. Consequently it was concluded that infection from unsterilized skin could not be introduced through the needle. One of the researchers has performed another study in which best practice was checked for the WHO in relation to the prevention of injection related infection[8].

Swabbing of clean skin before injection was found to be unnecessary.Despite these results; there is a lack of research to create a solid evidence base for skin cleansing before an intramuscular injection is administered. The use of alcohol swabs is a standard procedure for skin preparation before injection in hospitals. Yet most of the organizations do not prescribe alcohol swabs for vaccination, and boiled swabs are used to prepare skin for immunization[9]. But WHO has stated not to use cotton balls stored in a multiuse jar, and it is also pointed out by PGIMER, Chandigarh's infection control committee.And no clearly clean skin should be swabbed before injection as recommended by WHO. The objective of the study was to compare the risk of local skin infection by preparing an injection site with boiled cotton swabs, alcohol swabs and no clearly clean skin swabbing for DPT / combination vaccines among infants at Advanced Paediatric Centre, PGIMER, Chandigarh[10].

Figure 1. Use of alcohol swab before and after injection

In the figure 1 it is shown that how the alcohol swab is used before and after the injection. This has shown first you have to clean the skin where you want to give the shot followed by the pinch and inserting the needle into the skin. After injecting the skin press an alcohol swab gently on the spot where the shot was given.

MATERIALS AND METHOD

An experimental design was adopted for evaluating the risk of infection at the injection site using the three methods of preparation of the injection site. The conditions for inclusion were infants who received DPT / combined vaccines.The research was carried out in the environment of Immunization, Advanced Paediatric Centre, PGIMER, and Chandigarh. There were three approaches used before DPT / combination vaccines to prepare the injection site.

Preparing site for injection using boiled cotton swabs, preparing site for injection using alcohol swabs, No clearly clean skin swabbing was observed.The research sample was collected from July-October 2014 using complete enumeration sampling technique. For the analysis the sample size was 450 samples (150 in each group). The allocation was per day randomization by node.The vaccine is carried out regularly, i.e. 6 days a week. Alternatively every protocol according to the randomization was implemented. The randomization numbers were created by computers and sealed in opaque envelopes.Before injection administration, the skin preparation methods were spread over the different days of the week.

The devices, i.e. interview schedule and observational checklist, and three protocols for skin preparation, were prepared from literature review and validated by nursing and pediatric experts.Checklist of findings contained multiple signs suggesting local skin infection. The checklist had contained a total of 15 symptoms. Symptom severity was measured after immunization according to adverse events, and specific terminology requirements for adverse events.

Grade 1 infection means any sign of tenderness with or without warmth or edema or 100.4 ° F101.1 ° F or nodule or rash.Grade 2 infection means either of the symptoms-pain or edema or lymphadenopathy or reduced movement of the limbs or constant vomiting or fever 101.2- 102.0 ° F or cellulitis. Grade 3 infection indicates the occurrence of any of the 102.1- 104 ° F symptoms-abscess or fever.Inter-rater approach was used to test the reliability of the instruments. On the same subject two raters administered the same devices. The method has been tested on five subjects. The reliability of the inter rater was tested using the index Cohen Kappa. Kappa index was found to be accurate with 0.95.ANMs have been educated and trained in the application of three skin care methods procedural protocols.The parents were informed at first contact with the researcher about implementing the observational checklist to recognise the signs of infection at the injection site.

The parents' statements have been checked by asking them to apply the observational checklist and record the symptoms by telephone.

The researcher then visited the house to test the reliability of observations from parents. Cohen Kappa has been measured for validity test. 60 random homes were visited and 55 agreements and 5 disputes were reached between the investigator and his kin. It was found that Cohen kappa is 0.913 which indicates good agreement with the p value < 0.001.The data were gathered in July-October; 2014. Parents / guardians of each study subject enrolled were given informed consent. The data was collected from the parent / guardian using the interview plan.During the time of vaccination their address and telephone numbers were obtained at first contact with parents. ANM administered the DPT / Combination Vaccine under the supervision of the Principal Investigator using the three protocols.

The checklist was used in post-procedural follow-ups from day 1 to day 7 to test for local skin infection, i.e. a week or before the parents subsided the infection.From the same day to the 7th day of vaccination or until the infection subsides, the parents were contacted by telephone, and were asked to follow the observational checklist and record the different symptoms contained in the observational checklist.Calculations were rendered using software SPSS 16.0. The data were analysed using statistics of concise and inferential type.Specific statistical methods were used such as central trend measurements, dispersion measurements,

percentages and parametric tests i.e. ANOVA and repeated measure ANOVA and the results were interpreted and presented using tables, diagrams and graphs.

In the above dataset we have shown how the sample dataset pass through different steps, the randomization is applied and finally ANOVA test is perform to compute the results.

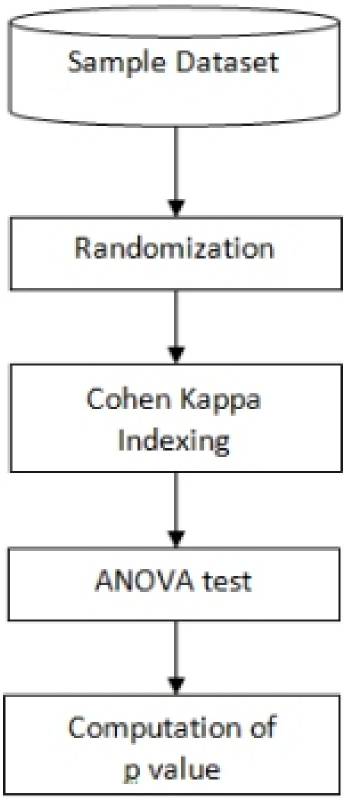

Figure 2. Block diagram of proposed work

RESULTS

The socio-demographic profile of infants is shown in Table 1. The subjects of the study had been distributed equally in each arm. Between the subjects of the boiled swab arm and alcohol swab arm most were below 4 months of age. 46 per cent of the research participants were below 2 months of age in the no swabbing arm as well as in the 2-4 month age range. All three of the arms had a higher proportion of males.The samples of the study were in the range of 1.93-8.17 kg with a mean weight of 4.58±1.323 in the boiled swab arm, 1.90-7.63 kg with a mean weight of 4.62±1.322 in the alcohol swab arm, and 2.10-7.95 kg with a mean weight of 4.83±1.353 in the no swab arm of the preparation of the injection site prior to injection.For age, gender and weight all three arms were homogeneous. (P value > 0.05 per chi square test).

Table1: Socio demographic profile of child. N= 450

Sample characteristics	Methods of injection site preparation before injection			X^2df p value
	Boiled Swab (n=150) n (%)*	Alcohol Swab (n=150) n (%) **	No Swabbing (n=150) n (%) ***	
Age of child (months)				
<3	75 (51.7)	71 (45.7)	68 (45.0)	5.145
3-6	68 (45.0)	70 (45.6)	698(45.0)	4
>5	6 (3.4)	11 (6.8)	132(8.1)	0.277
Sex				0.549
Male	90 (60.0)	95 (64.6)	95 (65.0)	2
Female	60 (40.0)	55 (38.4)	55 (35.0)	0.747
Weight of child (kg)				
<2.61	8 (5.3)	9 (6.1)	5 (3.4)	5.976
2.61-4.61	73 (48.7)	65 (45.0)	61 (41.0)	5
4.62-6.61	56 (37.3)	62 (41.7)	63 (42.3)	0.241
>6.62	13 (8.7)	15 (9.4)	24 (14.4)	

Age (months): Mean± SD (range) - * 1.96± 1.071 (1.12-8), **2.35 ± 1.148 (1.11-5.31), *** 2.14 ± 1.226 (1.20-6.10),Weight (kg): Mean± SD (range) - * 4.68± 1.343 (1.94-8.18), **4.72 ± 1.332 (1.80-7.43), *** 4.43 ± 1.343 (2.20-7.85).

Socio Demographic Profile of Parents:

Most parents had been educated up to and above the secondary level. In most cases, in the three arms the mother's occupation was house wife and almost half of the fathers were professionals.The parent's mean income in the boiled swab arm was Rs.25007± 23835.91 with a range of Rs.4000-150000. While the income range in the second arm, (alcohol swab), was Rs.3000-1000000 with mean income Rs.20627± 19083.81.In no swabbing arm the parent's monthly income was in the Rs.3500-175000 range with mean income Rs.25207± 27727.36.All the classes were of a homogeneous type for parents' educational and occupational status and family monthly income (p value > 0.05 as per the chisquare test).Many of the research subjects in all three arms of the research were treated with pentavac and simple five.

Half of the test participants in the three arms of the test obtained the 1st dose of vaccine.The results shows the homogeneity of all three classes for vaccine type given and vaccine dose (p value > 0.05 as per chi-square test).

Symptoms Reported by Parents Telephonically:

Nearly all the subjects of the study had fever on day of vaccination which was reduced to half on day 1. On the day of the vaccination only intermittent crying was present. Redness, tenderness, swelling occurred on the same vaccination day, and decreased on day 1.Very few (2.6 percent) subjects in the boiled swab arm had painless nodule formulation and resolved by 10th-25th day of vaccination. At the injection site, 2.0 percent of subjects in the alcohol swab arm had developed painless nodule and resolved it by the 15th -20th day of vaccination.Though 0.6 per cent of subjects in no swabbing category had painless nodule that was resolved after vaccination by 25th day.

Intensity Infection Among Subjects:

Table 2 compares infection severity among three preparation arms for the injection site. 4.6 per cent of subjects had no infection on the day of vaccination, 78.6 per cent had Grade 2 infection and 16.6 per cent had Grade 1 infection in the boiled swab arm.While 2.6% had no infection in alcohol swab neck, 27.3 had Grade 1 infection and 70.0% had Grade 2 infection.

Table 2: Intensity of infectionamong subjects. N=450

Days	Intensity of infection	Methods of injection site preparation before injection			χ^2 /Fisher Exact df p value
		Boiled swab (n=150) n (%)	Alcohol swab (n=150) n (%)	No swabbing (n=150) n (%)	
Day 1	No infection Grade 1 Grade 2	7 (4.5) 25 (15.5) 118 (78.5)	4 (2.5) 41 (2763) 106 (70.0)	6 (4.2) 32 (21.2) 113 (74.4)	4.676 2 0.087
Day 2	No infection Grade 1 Grade 2	58 (45.3) 81 (54.0) 1 (0.5)	76 (50.1) 71 (46.3) 4 (2.5)	63 (41.0) 85 (56.3) 1 (0.7)	3.741 2 0.165
Day 3	No infection Grade 1 Grade 2	140 (93.3) 10 (5.5) -----	147 (91.3) 12 (8.2) 1 (0.5)	136 (91.5) 13 (8.7) ----	1.840 2 0.413**
Day 4	No infection Grade 1	145 (97.3) 4 (2.5)	145 (96.0) 6 (4.2)	148 (99.0) 3 (2.2)	1.129 2 0.677*
Day 5-8	No infection Grade 1	145 (97.3) 4 (2.5)	147 (99.0) 3 (2.1)	148 (99.2) 1 (0.7)	1.770 2 0.547*

*Yates correction **Fisher Exact

4.0 per cent had no infection in either swabbing arm, 21.3 per cent had Grade 1 infection and 74.6 per cent had Grade 2 infection. Half of the subjects had no infection on the 1st day after vaccination and nearly all of the subjects had no infection among the three arms by the next day.On the 7th day, 8 subjects had painless nodule that was resolved 10-25 days later. There was no statistically significant difference between the three arms in the severity of the symptoms (pvalue>0.05 as per chi-square test).

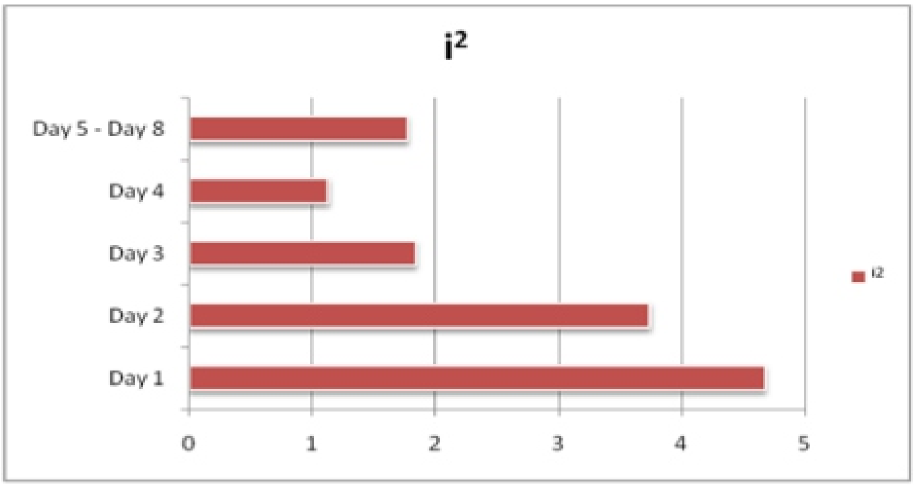

Figure 3. Comparison of i2 value day wise

Figure 3 has shown the comparison of i2 value on the basis of days. Here we have take 5 days observation in which first four are the days from day 1 to day 4 and the last day is rest of the days from day 5

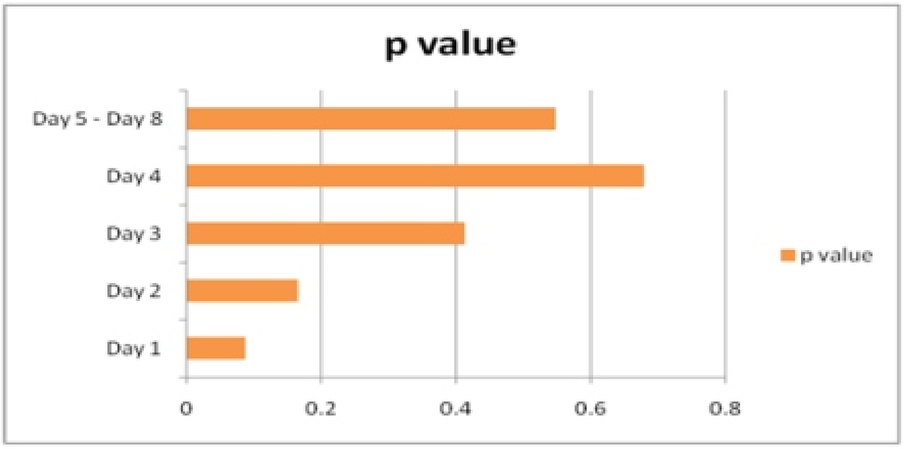

Figure 4. Comparison of p value day wise

Figure 4 has shown the comparison of p value on the basis of days. Here we have take 5 days observation in which first four are the days from day 1 to day 4 and the last day is rest of the days from day 5.

Comparison of Presence of Local Skin Infection after Vaccination between and within the arms:

Comparison of local skin infection after vaccination from day 0 to day 7 between the three arms i.e. boiled cotton swabs, alcohol swabs and no noticeably clean skin swabbing was performed and between the three arms.There was no statistically significant difference between and within the three arms in the presence of local skin infection after vaccination from day 0 to day 7 (p value > 0.05 as per ANOVA test).

Comparison of Presence of Local Skin Infection after Vaccination at Injection Site:

Table 3 shows a comparison of three of the arms boiled cotton swabs, alcohol swabs and no clearly clean skin swabbing for injection site preparation when infection occurs at the site of injection.Comparison of three research arms in pairs revealed that after vaccination between arms there is no statistically significant difference in local skin infection (p value>0.05 as per the Bonferroni and Dunnett T3 tests).

Table3: Comparison of presence of local infection after vaccination at injection site N= 460

(A) local infection at injection site	(B) local infection at injection site	Mean Difference (A-B)	p value*	94% Confidence Interval	
				Lower Bound	Upper Bound
Bonferroni					
Boiled cotton swabs	alcohol swabs	.012	1.02	-0.035	0.055
	no swabbing	.009	1.02	-0.037	0.054
Alcohol swabs	no swabbing	-.002	1.02	-0.047	0.043
Dunnett T3					
Boiled cotton swabs	alcohol swabs	.011	0.95	-0.038	0.058
	no swabbing	.009	0.96	-0.034	0.054
Alcohol swabs	no swabbing	-.002	1.02	-0.045	0.044

*Repeated measure ANOVA

Management of Fever and Care of Injection site:

Almost all of the study subjects were administered antipyretics in the three arms as stated by the parents. More than 3 doses were given in boiled swab arm 43.1 per cent.

Although more than 3 doses were given in alcohol swab arm and 44.5 percent in no swab arm, 37.4 percent were administered.Most participants in the sample were administered antipyretics in the three arms for two days. There was no important statistical difference between the three arms for number of antipyretic doses and number of days of antipyretic administration (p value > 0.05 as per chisquare test).

On the injection site, few subjects applied ice (7.3 percent) to relieve tenderness and discomfort in all three divisions of the study and 2.0 percent of subjects applied Vicks only in boiled swab arm. Among the three research weapons, the application was made for 2 days.There was no statistically significant difference in injection site treatment between the three arms (p value>0.05 as per chisquare test).

DISCUSSION

Injections are the most common procedures performed by nurses worldwide. It is important to keep it safe when delivering this form of injection, i.e. it should not affect the patient and the health care provider.In an attempt to keep the injections safe, the idea of planning for the injection site came into practice to employ control of infections.There are numerous guidelines followed by different health care agencies leaving nurses in an unclear position as to whether or not to clean the skin. In fact, there is a lack of evidence to show that whether swabbing or no swabbing at the injection site can lead to any infection.The present study was therefore conducted with the aim of comparing the risk of local skin infection with boiled cotton swabs, alcohol swabs and no visibly clean skin swabbing for DPT / combination vaccines among infants by preparing the injection site.Although there are guidelines for delivering the injections, each health care provider always practices what they are comfortable with. Thus, three separate guidelines for the three methods of skin preparation were established to ensure the uniformity in administering the vaccine.The ANM's have been educated and trained to apply the three procedural protocols. Re-demonstrations were held to ensure the protocols were implemented correctly.Parents are the best observers for earliest identification of any changes in their

infant. So the parents were informed at first contact about applying the observational checklist to recognise the signs of the infection and their hypothesis was confirmed.The follow-up was performed by phone to assess the signs of the infection using the parent's observational checklist. There are previous research that demonstrate the efficacy of telephone follow-up. The efficacy of telephone follow-up to predict the community's risk of orthopaedic surgical site infection has been assessed and a successful method of detecting infection was identified after hospital discharge.

CONCLUSION

The study indicates that there is no statistically significant difference in the initiation of injection site infection in three site preparation classes, i.e. boiled cotton swab, alcohol swabs and no clearly clean skin swabbing prior to injection.The idea underlying skin preparation before injection by wiping it with an alcohol swab as an antiseptic measure to prevent infection was critically examined in this study and it was found that the widely used technique was ineffective as a safeguard against infection.The study also showed that although the skin swabbing before injection significantly decreased the number of bacteria (skin flora), there was no significant difference between clinical signs and adverse local or systemic effects before intramuscular, intradermal and subcutaneous injections with or without alcohol swab preparation.

REFERENCES

[1] Centers for Disease Control and Prevention, "Manual for the Surveillance of Vaccine-Preventable Diseases," VPD Surveill. Man., 2012.

[2] J. Halbert, P. Kozarsky, J. Chiodini, N. Zwar, G. Brunette, and J. N. Zuckerman, "Vaccine-Preventable Disease," in Principles and Practice of Travel Medicine: Second Edition, 2013.

[3] I. F. Cook, "Sepsis, parenteral vaccination and skin disinfection," Human Vaccines and Immunotherapeutics. 2016.

[4] R. A. Khawaja, R. Sikanda, R. Qureshi, and R. J. M. Jareno, "Routine skin preparation with 70% isopropyl alcohol swab: Is it necessary before an injection? Quasi study," J. Liaquat Univ. Med. Heal. Sci., 2013.

[5] S. Rebelo Pacheco, C. Abadesso, A. Monteiro, and A. Taddio, "Pain management during childhood vaccination injections in Portugal – a call to action," Acta Paediatr. Int. J. Paediatr., 2016.

[6] H. J. Clothier, G. Selvaraj, M. L. Easton, G. Lewis, N. W. Crawford, and J. P. Buttery, "Consumer reporting of adverse events following immunization," Hum. Vaccines Immunother., 2014.

[7] H. Brody, "Choosing Wisely | Promoting conversations between providers and patients," ABIM Foundation, 2012. .

[8] E. R. Coon, P. C. Young, R. A. Quinonez, D. J. Morgan, S. S. Dhruva, and A. R. Schroeder, "2017 update on pediatric medical overuse a review," JAMA Pediatrics. 2018.

[9] V. Prasad and J. P. A. Ioannidis, "Evidence-based de-implementation for contradicted, unproven, and aspiring healthcare practices," Implementation Science. 2014.

[10] J. Bonhoeffer et al., "Template protocol for clinical trials investigating vaccines-Focus on safety elements," Vaccine, 2013

Barriers in Adherence to Diet in Patients with Type-2 Diabetes: A Literature Review

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ABSTRACT

Diabetes mellitus (DM) is one of the most difficult health problems of the 21st century. Poorly managed Type-2 diabetes is regarded as an important public health problem and is often related with negative outcomes. Adherence to prescribed treatment regimens and dietary recommendations are important for achieving positive health outcomes in DM management. Patient nonadherence can be a pervasive hazard to health and well-being, as well as a significant financial burden. This focus of this review paper is on the barriers in adherence to diabetic diet management plan among adults with Type-2 diabetes in India. The objective of the review was to determine the prevalence of Type-2 diabetes and the impact of knowledge, perceptions, and sociocultural factors in adherence to diabetic diet among the people with Type-2 diabetes mellitus (T2DM).

Despite the fact that several research outcomes have demonstrated the importance of diet management and glycaemic control in D2M management, the adherence towards self-care and dietary recommendations among Indian patients remains unsatisfactory. The review clearly revealed the significance of the factors like knowledge, awareness, sociocultural and lifestyles related factors in the adherence to selfcare behaviours including dietary routines in diabetes management.

Keywords Barriers, dietary adherence, India, patients, self-care behaviours, type 2 diabetes mellitus.

INTRODUCTION

Globally, type -2 diabetes mellitus is considered as the most significant challenge faced by the health care systems of the 21st century. Diabetes mellitus is a significant health problem in the emerging economy like India. The problem of diabetes is high and rising, fuelled primarily by the rising prevalence of overweight/obesity and unhealthy lifestyles among people.[1] Diabetes ranks among the top ten leading causes of mortality in this century among adults, alongside other diseases like cardio-vascular diseases (CVD), respiratory diseases, and other fatal diseases including cancer.[1]

The recent data on the pervasiveness of diabetes and rapid increase in the prevalence of diabetes during the years between 2000 and 2030 is revealing startling information. The global incidence of diabetes mellitus was assessed as 2.8% across all age groups in 2000 and it is expected to increase upto 4.4% in 2030.[2] [3] It is anticipated that the total number of people with diabetes will surge from 1700 lakh in 2000 to 3660 lakh 2030.[2] Of the total diabetic cases, 90% of cases are accounted by Diabetes Mellitus Type 2. WHO reports that the pervasiveness of diabetes is increasing rapidly in countries with lower and middle incomes (WHO Report). Some of the risk factors attributed to the rapidity in the rise of diabetes included populatio explosion, poor eating habits, and leading a sedentary lifestyle also play a significant role in the global rise of the diabetes epidemic.[4] Uncontrolled diabetes increases the problems associated with vascular, macro-vascular and micro-vascular diseases including diabetic nephropathy, diabetic retinopathy and neuropathy complications.[5] Since 1990, the pervasiveness of diabetes in India has increased steadily, and since 2000, it has accelerated dramatically. IDF's Figure 1 depicts the growing trend in diabetes incidences in India over the previous decades.

Diabetes prevalence in India has increased from 7.1% in 2009 to 8.9% in 2019.

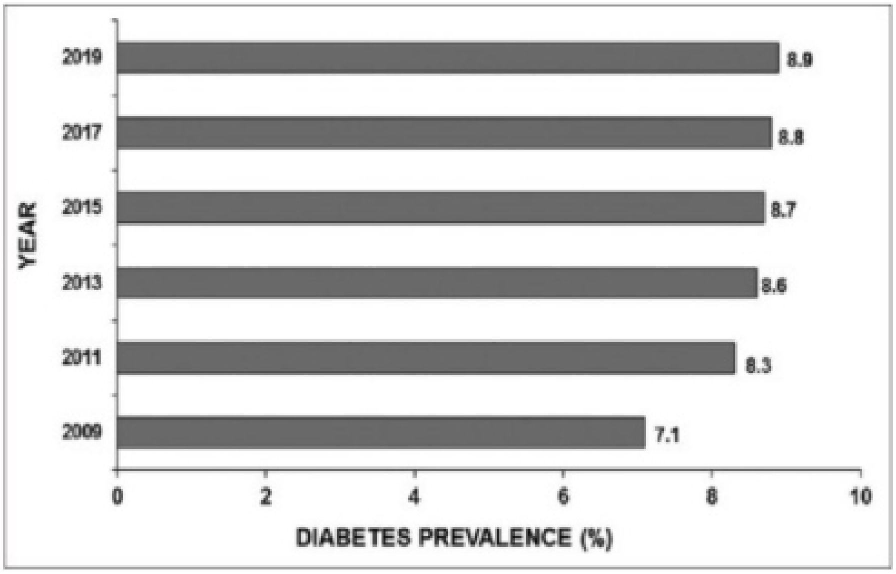

Figure 1. Diabetes prevalence in the recent decade.[3]

IMPORTANCE OF DIETARY ADHERENCE IN DM MANAGEMENT

The process of following to a diet plan while keeping one's motivation intact and warding off slips into old eating habits is referred to as dietary adherence. Antecedents that enhance diet adherence include motivation, comprehension of nutritional advice, formation of healthy health attitudes, self efficacy, establishing realistic objectives, and social support. Successful diet adherence has a positive impact on health, as shown by improved clinical parameters specific to T2DM and increased health-related quality of life.[6] The patient's active engagement in self-care behaviours, The patient's active engagement in self-care behaviours, such as committing to the suggested diet, participating in regular exercise, and ingesting prescribed medicines, is critical to the treatment of type 2 diabetes.[7] [8] Patients' attitudes, belief toward treatment regimen, and overall perception towards T2DM have an effect on their adherence to diabetes treatment plans and changes in lifestyle.[9] The management of the D2M disease relies heavily on the patients' observance of the prescribed diet.[10] Dietary modification is often advised as the first step in the therapy of type 2 diabetes, however despite the fact that it is considered to be the most difficult component of diabetes management, [11] it has been argued that it is the cornerstone of diabetes management.[12]

Patients' ability to remain committed to a healthy diet may be impacted by elements related to their culture, religion, social environment, and individual choices.[9] A study done by in New Zealand has revealed that only 22% of diabetic patients have reported following the diabetic diet strictly as per the recommendations by physicians. [13]

In a survey conducted in the United States, it was observed that 65% of diabetic participants followed the recommended protein diet, only 28% of diabetic participants followed the recommended saturated fat diet and only 18% of diabetic participants followed the recommended fibre intakes inregular diet.[14] 81.4% of diabetic patients in Jordan, a developing nation, were not adhering to the recommended dietary regimen. [15] It was reported that inspite of the beneficial effects of lifestyle modifications and dietary adherences programs on diabetes management, adherence decreases over time due to the necessity to alter long-followed lifestyle patterns. [16]

METHOD

Between January 2023 and March 2023, an in-depth literature search was undertaken in several online repositories and medical databases like PUBMED, EMBASE, Google Scholar, National Library of Medicine's (NLM) MEDLINE; Elton B. Stephens CO's (company) (EBSCO) - CINAHL; SCOPUS, ScienceDirect, PsycINFO, Cochrane library, etc. to identify studies that focussed on factors influencing non adherence to selfcare behaviours in general and non adherence to diabetic diet in particular among patients with T2DM. As an outcome of the review, several studies related with "Barriers in Adherence to Diet in T2DM Patients" was identified and the key outcome and findings of these studies are discussed in this review.

STUDIES ON BARRIERS IN ADHERENCE TO DIABETIC DIET

An evaluation was done on the barriers preventing patients with T2DM from following dietary recommendations using focus groups (6-12 participants) and surveys (446 respondents) in different medical centres in urban and suburban areas in US. The study extracted all feedbacks pertinent to challenges and barriers that impacted patients' ability to adhere to the suggested diet. The study found that the moderate diabetic diet was perceived to be a greater burden than oral agents, but less burdensome than insulin. On the other hand, a stringent weight loss diet was rated as equally burdensome as insulin. Despite this, self-reported medication and insulin adherence was significantly higher than moderate diet adherence. The study identified that the cost of diabetic diet was the most frequently cited barrier in the focus groups. Other important perceived barriers were small sized portion of diet, support from the family, and quality of life and modification in lifestyle. Patients from the urban region reported higher difficulty interacting with their provider regarding modifications in diet requirements and also social circumstances, as well as a problem with a diabetes diet's regimented schedule. [17]

A study has been carried out with 540 patients with T2DM on dietary habits from six Italian diabetes centres. The study measured three-day diet record of the diabetes patients. Diet records were examined using Italian food composition tables. The study found that the average consumption pattern with regard to different nutrient were near close to the prescribed level. Upon further analysis of the dietary regimen, it was identified that the saturated fat and fiber intakes were the least representative of the dietary target. The analysis revealed that saturated fat was greater than 10 percent of total calories in 43 percent of patients, fiber intake was 20g per 1000kcal in only 6% of patients, and it was 15 g/1000 kcal in 25% of patients (acceptable). These findings suggest that even in Italy, dietary recommendations are not always followed to the letter. Given the diabetic population's high BMI, calorie intake is slightly higher. [18]

Based on the outcome of a focus group study with 516 patients diagnosed with T2DM, Booth et al. [19] have proposed that the obstacles in the self-management of diabetes disease and diet adherence could categorised into six groups: “Challenges involved in breaking long-standing routines”, “perceptions that are not positive towards the "new" or advised treatment plan”, ‘obstacles that are rooted in one's social environment”, “inadequate levels of awareness and comprehension”, “lack of motivation”, and “hurdles stemming from the logistical challenges of implementing lifestyle modifications”.[19]

In a research that used a cross-sectional approach, found that 49.2% of patients with T2DM in Nepal had a poor understanding of the suggested diet for their condition. The research also indicated that male participants adhered to dietary recommendations more than female participants. Those diabetic patients who resided closer to the hospital had a better rate of adhering to the dietary recommendations given to them by their physicians, as well as those given by their nuclear families, rather than those given by their joint or extended families. The degree to which individuals followed dietary recommendations declined with advancing age and was shown to have a positive correlation with their level of diabetes awareness. A positive family history of diabetes was associated with a greater level of physical activity compliance compared to other people. In a similar vein, respondents from extended families or upper middle socioeconomic classes displayed stronger dietary adherence than those from lower socioeconomic classes or nuclear or joint families. Patients who had been divorced were less likely to adhere to dietary management and physical activity recommendations than patients who had been married or widowed. [20] An evaluation was done on the perceived facilitators, barriers, and patient expectations in T2DM self-management. Patients were recruited at the outpatient clinic of the Portuguese Diabetes Association using a convenient sampling technique. Using video-recorded focus groups, qualitative data was collected. The study has identified three main themes: diet, physical activity, and glycemic control. There are four basic kinds of dietary change barriers that have been discovered, and these include decisional, quality of food, food amount, and dietary routine. In addition to variables relating to decision-making, physical activity was hampered by factors such as exhaustion, discomfort in the muscles and joints, and other co-morbidities. Across all three categories, information and the translation of knowledge, as well as familial and social relationships, were investigated and considered as facilitators in some circumstances and impediments in others. This research highlighted the value of customised counselling by providing fresh insight into the challenges, facilitators, and predicted results of type 2 DM self-management. [21] . In a study with 385 patients with diabetes, Patients who have diabetes often have problems determining the appropriate diet for them, both in terms of its quality and its quantity. A patient's food choices, adherence to the diet, and overall eating pattern may all be affected by their knowledge of a specified diet. A 67 item Food Frequency Questionnaire (FFQ) was used to examine the dietary routine and pattern of nutrition intake in T2DM patients. [22]

Observational cross-sectional study and identified the significant barriers in adherence to recommended diet in patients with T2DM. 126 volunteers with type 2 diabetes who were overweight or obese and had previously received nutritional counselling for a period of at least one year from two diabetes clinics in Tabriz, Iran were used as the sample in this study. The main components of dietary nonadherence were identified using factor analysis method. Seven barriers in dietary adherence were identified that included situational barriers and the inability to resist temptation; stress-related eating disorder and expense; difficulties with meal and snack planning; perplexity; work-related concerns; small portion size; and the absence of palatability and family support. According to the findings of the research, people with T2DM experienced certain challenges to adhering to their diet. It is expected that increasing dietary adherence among type 2diabetes patients in Iran would need taking into account and eliminating these obstacles in the context of dietary counselling. [10]

There is a scarcity of information on the amount of adherence to dietary guidelines and the challenges that people with type 2 diabetes face across Africa, especially Ethiopia. They undertook a study with the goal to determine the degree of dietary adherence and associated obstacles among type 2 diabetes patients in northwest Ethiopia. Adherence with diabetic dietary regimen was measured using “Perceived Dietary Adherence Questionnaire” (PDAQ). The findings reveal that a large number of the research participants (74.3%) did not follow the dietary guidelines. The question about eating high-sugar meals had the highest mean score. Based on the mean score, it was found that the participants seldom consumed fruits and vegetables and meals high in omega-3 fats. According to the survey, the most prevalent reasons for poor dietary compliance were a dearth of knowledge, an absence of dietary knowledge, an inability to pay the price of a healthy diet, and an absence of understanding of the advantages of dietary recommendations.

In multivariate logistic regression, a poor educational level, the prevalence of co-morbidities, an absence of prior

exposure to nutritional teaching, and a low monthly income were all statistically significant factors associated with non adherence. It was shown that individuals with type 2 diabetes in the northwest region of Ethiopia had a high risk of not adhering to the dietary guidelines. As a result, individualised health education on the possible benefits of good dietary guidelines in blood glucose management is advocated. In patients with T2DM, healthcare practitioners has to be upbeat in encouraging them to follow dietary guidelines . [23]

A study have explored the factors that influence self management in patients with T2DM. Semi-structured qualitative interviews were conducted with ten patients and four general practitioners as well as three practising nurses in a suburb region of Sydney, Australia. [24] The interviews were subjected to a theme analysis, and the socio-ecological model was used as a classification framework for the findings. Inductiv analysis of the text's meaning allowed for the discovery of additional themes not immediately apparent.

The levels of the socio-ecological model that influenced self-management were individual (literacy in e-health, selfmotivation, time constraints), interpersonal (family members, friends, diabetes education, relationship between patient and provider), community (culture, resources for self management) and organisational (affordability, multidisciplinary care). To handle this vast variety of elements, which are beyond the purview of specific services or organisations, there is a need for multilayer methods.

Examples ofsuch strategiesinclude tailoring health education and resources to the literacy and culture of e-health, putting an emphasis on social networks and the interaction between patients and healthcare providers, and simplifying access to cost-effective on-site allied health services.[24]

The styudy was conducted qualitative research using content analysis as their method for investigating the factors that prevent patients with T2DM in Iran from adhering to dietary guidelines. Data for the research were gathered by conducting 38 unstructured in-depth interviews with a total of 33 Type 2 Diabetes patients and the treatment supervisors who worked with them. The method known as "thematic analysis" was used in order to identify the categories and themes that emerged from the data. The COREQ Checklist was used to ensure that the research was as rigorous as possible. The findings of the analysis of the collected data have shown the creation of five kinds of perceived barriers, which are as follows: social concerns and disputes, family eating behaviours, inadequate social support, social impasses, and dominant food patterns. [25]

From a tertiary hospital in Singapore have examined the relationship between nutrition knowledge related with diabetes and quality of diet with 42 participants.. Twenty-one semi-structured interviews were recorded, and analysed to determine perceived barriers and enablers in the adherence toward dietary recommendations. The research used theme analysis to identify six barriers that make it difficult to adhere to dietary instructions. These obstacles were an obesogenic situation, an insufficient amount of time, a conflict between instructions and personal beliefs, emotional stress from external factors, a lack of personal motivation. The research also identified the four facilitators in sticking to dietary rules, which are personal drive to better condition, fear of T2DM consequences, adequate DRNK, and the existence of social support. [26]

A qualitative study was carried out to investigate the perspectives, practises, and barriers to self-care practises among urban Pakistani adults with T2DM. The participants of the study included thirty-two adults with T2DM from a hospital in Lahore. Using qualitative research approach and semi-structured intervie s, the researcher generated six overarching themes from the thematic analysis. The themes identified were patients' knowledge of diabetes, consequences of diabetes and other comorbidities, the burden of self-care, and living circumstances. The involvement of family and friends was found to be as important as the role of doctors and healthcare providers. According to the findings of the research, some of the most important barriers to self care are financial restrictions, physical limit tions, harsh weather conditions, social events, a passion for food, forgetfulness, a fear of needles, and a hectic schedule. Bukhsh et al. [27]

A Study examined diabetic patients' knowledge of diabetic diet. A cross-sectional survey was carried out with one hundred T2DM patients. The study utilized a validated, and structured questionnaire. The study revealed that participants had limited knowledge about recommended diabetic diet. For the patient to adhere to a healthy diabetic diet, a higher level of knowledge is deemed necessary. [28]

CONCLUSIONS

The review clearly demonstrated that diabetes patients of majority of the studies have inadequate level of awareness and knowledge toward dietary patterns in the management of diabetics. In addition, socio-cultural, lifestyles related factors were identified as the strong barriers in adherence to proper diabetes management practices and dietary recommendations. There is a strong need to embark empirical research to explore the influence of these factors with the management of T2DM among patients. Majority of the respondents have failed to follow the self care practices including dietary management prescribed to alleviate the complications of the ailment. The studies on diabetic diet adherence shows that majority of the patients lacked knowledge on diet modification to improve the diabetic recovery. Similarly, diabetes patients of the studiesoften show negligible interest toward adherence to prescribed diet and practices.

The study recommends that a comprehensive policy may be enacted to educate and train diabetes patients on the awareness, management and control of the diabetes and different met ods to keep track of the treatment process.

Further, diabetes awareness campaign could be conducted periodically to educate and mitigate the harmful impacts of this disease. Thisstudy is a part of the major study on diabetes awareness, knowledge, and adherence to dietary practices among diabetic patients in rural area. The study has major implications in understanding on the actions that could be potentially suggested for modifications in dietary habits, lifestyle changes to T2DM patients in rural areas.

The results of thisliterature review clearly revealed that the predominant dietary patterns play a significant role in patients' diet adherence. Patients' dietary habits may be traced back to the cultural, environmental, social, and religious influences of their respective societies. Thus, effective health education enhances knowledge, attitudes, and behaviours, especially with relation to dietary habits and lifestyle changes, which leads to improved glycemic control and may delay the onset of diabetes while preventing complications down the line. Providers of healthcare must ensure that patients comprehend the concept of diet adherence and incorporate it into their daily lives.[6] Dietary adherence and its components require additiona study in order to develop more effective communication strategies for T2DM patients.

Overall, the findings emphasise the need for a multidimensional approach in the control and management of T2DM and the promotion of a healthy diet among diabetics.

REFERENCES

[1] Pradeepa R, Mohan V. Epidemiology of type 2 diabetes in India. Indian journal of ophthalmology. 2021 Nov;69(11):2932.

[2] Wild S, Roglic G, Green A, Sicree R, King H. Global prevalence of diabetes: estimates for the year 2000 and projections for 2030. Diabetes care. 2004 May 1;27(5):1047-53.'

[3] Cho NH, Shaw JE, Karuranga S, Huang Y, da Rocha Fernandes JD, Ohlrogge AW, Malanda BI. IDF Diabetes Atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045. Diabetes research and clinical practice. 2018 Apr 1;138:271-81.

[4] Pradeepa R, Mohan V. Prevalence of type 2 diabetes and its complications in India and economic costs to the nation. European journal of clinical nutrition. 2017 Jul;71(7):816-24.

[5] Susan van D, Beulens JW, Yvonne T. van der S, Grobbee DE, Nealb B. The global burden of diabetes and its complications:an emerging pandemic. European Journal of Cardiovascular Prevention & Rehabilitation. 2010 May 1;17(1_suppl):s3-8.

[6] Al-Salmi N, Cook P, D'souza MS. Diet adherence among adults with type 2 diabetes mellitus: A concept analysis. Oman Medical Journal. 2022 Mar;37(2):e361.

[7] Jordan DN, Jordan JL. Self-care behaviors of Filipino American adults with type 2 diabetes mellitus. Journal of Diabetes and its Complications. 2010 Jul 1;24(4):250-8.

[8] Reisi M, Javadzade H, Mostafavi F, Jalilian F, Mahaki B, Sharifirad G. Effect of theory based education on blood sugar control in type-2 diabetic patients. Iranian Journal of Endocrinology and Metabolism. 2017;18(6):420-31.

[9] Alsairafi ZK, Taylor KM, Smith FJ, Alattar AT. Patients' management of type 2 diabetes in Middle Eastern countries: review of studies. Patient preference and adherence. 2016 Jun 10:1051-62.

[10] Halali F, Mahdavi R, Mobasseri M, Jafarabadi MA, Avval SK. Perceived barriers to recommended dietary adherence in patients with type 2 diabetes in Iran. Eating behaviors. 2016 Apr 1;21:205-10.

[11] Chechlacz M, Rotshtein P, Klamer S, Porubska K, Higgs S, Booth D, Fritsche A, Preissl H, Abele H, Birbaumer N, Nouwen A. Diabetes dietary management alters responses to food pictures in brain regions associated with motivation and emotion: a functional magnetic resonance imaging study. Diabetologia. 2009 Mar;52:524-33.

[12] Nagelkerk J, Reick K, Meengs L. Perceived barriers and effective strategies to diabetes self-management. Journal of advanced nursing. 2006 Apr;54(2):151-8.

[13] Broadbent E, Donkin L, Stroh JC. Illness and treatment perceptions are associated with adherence to medications, diet, and exercise in diabetic patients. Diabetes care. 2011 Feb 1;34(2):338-40.

[14] Resnick, H.E., Foster, G.L., Bardsley, J. and Ratner, R.E., 2006. Achievement of American Diabetes Association clinical practice recommendations among US adults with diabetes, 1999–2002: the National Health and Nutrition Examination Survey. Diabetes care, 29(3), pp.531-537.

[15] Khattab M, Khader YS, Al-Khawaldeh A, jlouni K. Factors associated with poor glycemic control among patients with type 2 diabetes. Journal of Diabetes and its Complications. 2010 Mar 1;24(2):84-9.

[16] Yoo JS, Lee SJ, Lee HC, Kim MJ. The effect of a comprehensive lifestyle modification program on glycemic control and body composition in patients with type 2 diabetes. Asian Nursing Research. 2007 Sep 1;1(2):106-15.

[17] Vijan S, Stuart NS, Fitzgerald JT, Ronis DL, Hayward RA, Slater S, Hofer TP. Barriers to following dietary recommendations in Type 2 diabetes. Diabetic medicine. 2005 Jan;22(1):32-8.

[18] Rivellese AA, Boemi M, Cavalot F, Costagliola L, De Feo P, Miccoli R, et al. Dietary habits in type II diabetes mellitus: how is adherence to dietary recommendations?. European journal of clinical nutrition. 2008 May;62(5):660-4.

[19] Booth AO, Lowis C, Dean M, Hunter SJ, McKinley MC. Diet and physical activity in the self-

-management of type 2 diabetes: barriers and facilitators identified by patients and health professionals. Primary health care research & development. 2013 Jul;14(3):293-306. [20] Parajuli J, Saleh F, Thapa N, Ali L. Factors associated with nonadherence to diet and physical activity among Nepalese type 2 diabetes patients; a cross sectional study. BMC research notes. 2014 Dec;7:1-9.

[21] Laranjo L, Neves AL, Costa A, Ribeiro RT, Couto L, Sá AB. Facilitators, barriers and expectations in the self-management of type 2 diabetes—a qualitative study from Portugal. European Journal of General Practice. 2015 Apr 3;21(2):103- 10.

[22] Shikur, ADB, Hagos, MS, Yifter, DH. Dietary pattern of type 2 diabetes mellitus patients on follow up in public hospitals Addis Ababa, Ethiopia. Master's Thesis. Addis Ababa University. 2016.

[23] Ayele, A.A., Emiru, Y.K., Tiruneh, S.A., Ayele, B.A., Gebremariam, A.D. and Tegegn, H.G., 2018. Level of adherence to dietary recommendations and barriers among type 2 diabetic patients: a cross-sectional study in an Ethiopian hospital. Clinical diabetes and endocrinology, 4(1), pp.1-7.

[24] Dao J, Spooner C, Lo W, Harris MF. Factors influencing selfmanagement in patients with type 2 diabetes in general practice: a qualitative study. Australian journal of primary health. 2019 May 14;25(2):176-84.

[25] Mostafavi-Darani F, Zamani-Alavijeh F, Mahaki B, Salahshouri A. Exploring the barriers of adherence to dietary recommendations among patients with type 2 diabetes: A qualitative study in Iran. Nursing Open. 2020 Nov;7(6):1735- 45.

[26] Han CY, Chan CG, Lim SL, Zheng X, Woon ZW, Chan YT, Bhaskaran K, Tan KF, Mangaikarasu K, Chong MF. Diabetes related nutrition knowledge and dietary adherence in patients with Type 2 diabetes mellitus: A mixed-methods exploratory study. Proceedings of Singapore Healthcare. 2020 Jun;29(2):81-90.

[27] Bukhsh A, Goh BH, Zimbudzi E, Lo C, Zoungas S, Chan KG, Khan TM. Type 2 diabetes patients' perspectives, experiences, and barriers toward diabetes-related self-care: a qualitative study from Pakistan. Frontiers in endocrinology. 2020 Nov 27;11:534873.

[28] Hansaram, Sinha, AP, Chongloi, N, Sahoo, B, Ara, M, Savita, Madanlalsaini. A Cross-Sectional Study to Assess the Knowledge of the Diabetes Patients Regarding Diabetic Diet. Indian Journal of Nutrition. 2022 Feb 25; 9(1): 250.

A Brief Review on Queue Management Systems for Different Applications

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ABSTRACT

Queue management technology helps to reduce actual and predicted customer wait times, improve customer satisfaction, and provide the data to your managers needed to further optimize service, Queue Management System (QMS)presents a viable solution for different applications. It is employed to manage lines in a queue area in a variety of circumstances and locales. The article discusses the concepts of Queue Management Systems for Hospitals, Satellite Networks Based on Traffic Prediction, using Deep Neural Networks (DNN). Managing high patient loads in tertiary care hospitals represents a significant challenge in streamlining health service delivery. At several hospital service locations, including the registration, lab, and bill payment counters, patients must frequently wait in line. In these circumstances, Queue Management Systems (QMS) offer a practical patient management option. Satellite Internet the Adaptive Random Early Detection (ARED) queue management algorithm is proposed to be improved by traffic prediction based on a dynamic triple exponential smoothing model, smoothing coefficient optimization of the model using a differential evolutionary algorithm, and a cubic function based on traffic prediction. Customers and the administrative staff of the company can use a queue management system that uses the Open-CV platform and CNN algorithm for image processing, together with real-time person detection and people count recording. This essay also discusses several techniques in relation to their applications. With services that have medium to lengthy waiting periods, the proposed method seeks to reduce customer discontent.

Keywords Adaptive random early detection, CNN image processing, cubic function, differential evolution algorithm, dynamic triple exponential

INTRODUCTION

A queue management system is a strategy for managing lines of people in various settings and queuing areas. Queuing theory is the study of how queues are formed and spread. Doctor's offices, access to diagnostic procedures, specialist referrals, airport check-in, baggage claim, runway delays, waiting for landing, growing traffic, etc. are some typical settings where queueing theory is applied. Long wait times in clinics, hospitals, and emergency rooms (ER) may make treatment unaffordable for sick patients and encourage irrational behavior, such as patients leaving the hospital without receiving care, which may result in treatable diseases becoming incurable and unavoidable negative outcomes. According to studies, prolonged wait times in emergency departments cause stress for both patients and the employees who work there. They also frustrate patients who visit there. According to studies, prolonged wait times in emergency departments cause stress for both patients and the employees who work there. They also frustrate patients who visit there. Currently, the US government is concerned with providing quality health care and wellness for its citizens, which is not consistent with the effect of extended waiting times. This is the rationale behind this review of the management of extended waiting times in emergency rooms. In order to manage diverse service-based work owes in hospitals, the author suggests a thorough mobile- enhanced queue management system. The proposed system includes full patient counters, hospital pharmacies, waiting areas, and laboratories. The system is appropriate for usage without specialized hardware support because it is built using interfaces on mobile devices and smart displays. The suggested system includes a novel feature called crowdbased token production at numerous counters, where tokens are produced dependent on the number of tokens served at that counter. In high-traffic situations, which are frequent ingovernment healthcare institutions in India, this might aid in crowd control. The system is also anticipated to handle several token generations at a single counter, which could be used for cases where family members avail healthcare services. The system also supports seamless queue management between different service areas (for example registration and doctor visits) by transferring the queue number from the registration desk to the OPD area as well as for downstream services so that the patient does not need to generate/collect multiple tokens [1]. The self-closeness of satellite organization administrations is exaggerated in the long-range reliance on the traffic, which puts the entire hub network in a burst condition for a protracted period of time and has a substantial impact on queueing execution. The selfcomparison information stream is predictable, and the expected network traffic can foresee the burst state of queueing. The foundation of a high-accuracy traffic expectation model and an examination of a line-the-board calculation for satellite organizations given traffic forecast can thus control network blockage and limit line length ahead of time [2]. The great impediment looked at during the shrewd lining frameworks, for example, openness to a shifted client base, decreased cost of the organization, convenience utility, diminished the above and log jam related with misleading solicitations, should be evaluated with consideration. There is likewise a physiological obstruction for clients stressing that leaving the holding up region will without a doubt detach them from the framework causing the protracting holding up times upon return. Besides, the obliviousness in further developing the client experience regardless of the bother of administration with the holding up lines makes it unfortunate. Creating answers for the dreary errand of hanging tight for administrations is a basic need, particularly because of the developing interest as the number of inhabitants on the planet keeps on lifting.

Since web applications are currently coordinated inside the dynamic social orders, utilizing such a means to better lining frameworks is natural. From now on, we propose a snare of things to take care of the issue [3].

RELATED WORKS

Patient length-of-stay in the emergency department through dynamic queue management.

This includes the many Data Innovation (IT) frameworks and data sets that support the ED and its supporting divisions in carrying out their functions. For instance, processes from the ED work in tandem with those from the research center (such as blood tests) and the X-beam offices. Blood Framework and X-beam Framework are used individually in the cycles in the research facility and the X- beam offices. The findings of the two patient tests are contained in the Blood Framework and the X-beam Framework, respectively. These frameworks serve as the structural underpinnings of the ED cycle. The real-time frameworks provide data that is used to support both the scientific model and the choice assistance model[4].

Adaptive Active Queue Management Based on Model Predictive Control.

To design an AQM algorithm based on MPC, the traditional zero-order hold (ZOH) is used to discretize. Suppose the values of δp and δq are sampled in each interval Ts, then the transfer function which relates the δp and δq can be:[5]

$$G(z) = \frac{(m_1 z^{-1} + m_2 z^{-2})}{(1 + n_1 z^{-1} + n_z z^{-2})} z^{-d} \tag{1}$$

where d = dR T0s e is the system delay, m1, m2, n1, n2 are determined by the network parameters, and Ts as the following:

$$\begin{cases} m1 = \dfrac{C^3 R_0^3 \left(\left(2 - 2e^{\frac{-Ts}{R_0}} \right) N + CR_0 \left(-1 + e^{\frac{-2NTs}{CR_0^2}} \right) \right)}{4N - 2CR_0} \\ m2 = \dfrac{C^3 e^{-\frac{(2N+CR_0)Ts}{CR_0^2}} R_0^3 \left(2 \left(-1 + e^{\frac{Ts}{R_0}} \right) N - CR_0 \left(-1 + e^{\frac{-2NTs}{CR_0^2}} \right) \right)}{2(-2N + CR_0)} \\ n1 = -e^{-\frac{2NTs}{CR_0^2}} - e^{-\frac{Ts}{R_0}} \\ n2 = e^{-\frac{(2N+CR_0)Ts}{CR_0^2}} \end{cases} \tag{2}$$

Define the values of δp and δq as the input value u and output value y, respectively, then the dynamic model of TCP behavior can be described as the following input- output difference equation:

$$A(z^{-1})y(t) = z^{-d}B(z^{-1})u(t), \qquad (3)$$

where $A(z{-1}) = 1+n1z{-1}+n2z{-2}$, $B(z{-1}) = m1z{-1}+m2z{-2}$.

To derive the predictive value of δq after a jth interval, i.e., just its seconds later, a Diophantine equation is introduced:

$$A(z^{-1})E(z^{-1}) + z^{-j}F(z^{-1}) = 1, \qquad (4)$$

where E(z −1) and F(z −1) are the polynomials determined by A(z −1) and j, which can be expressed as E(z −1) = e0 + e1z−1 + ⋯ + ej−1z−(j−1), F(z−1) = f0 + f1z−1. Multiplying E(z −1) to the two sides of (7), we have:

$$: y(t+j) = z^{-d}B(z^{-1})E(z^{-1})u(t+j) + F(z^{-1})y(t). \qquad (5)$$

Let j = d +1, and transfer the above equation from the Z domain to the time domain, then

$$y(t+d+1) = f_0y(t) + f_1y(t-1) + g_1u(t) + g_2u(t-1)$$
$$+ \cdots + g_{d+2}u(t-d-1), \qquad (6)$$

where g1 = e0m1, g2 = m1e1 + m2e0, g3 = m1e2 + m2e1...gd+1 = m1ed + m2ed−1, gd+2 = m2ed. Note that y(t)= δq(t) = q(t)−q0, and the reference queue length is q (t + d + 1) = q0, so y (t + d + 1) = 0, then (10) can be simplified as:

$$u(t) = h_1y(t) + h_2y(t-1) + h_3u(t-1) + \cdots$$
$$+h_{d+3}u(t-d-1), \qquad (7)$$

where $h1 = -\frac{fo}{g1}$, $h2 = -\frac{fi}{g1}$, $h3 = -\frac{g2}{g1}$, …, $hd+3 = -gdg+12$. on

Hebb-learning theory to adjust the parameters hi (i = 1, 2,d + 3) shown . To make the equation easier to understand, rewrite as follows:

$$u(t) = K \sum_{i=1}^{d+3} w_i(t)\, x_i(t) \qquad (8)$$

Smart Mobile System for the Real-Time Tracking and Management of Service Queues.

The Internet of Things (IoT), which uses the being structure of cellphones to distribute tickets to visitors, is the cause of our smart line operation. Since the Arduino platform is open source and cheaply priced, we selected it. The customer opens the operation, scans the Near Field Communication (NFC) guard of the registering slave unit with their NFC-enabled smartphone, and then chooses whether to leave the staging area until they receive a visual and audible alert to return or stay and use the entertainment options in the app. To make the app screen more intuitive for the stoner, it is created to function as an actual status board.

In order to decrease erroneous service requests and improve the accuracy of the dynamic time vaticination algorithm, we specify a compass close to the requested service where the app may be utilized. For convenience, the drug users are also given the option to exchange their tickets. When a customer scans a ticket registration unit, the system process starts. The user can produce a ticket by scanning the QR code on it if they do not have an NFC-capable smartphone. The app then starts up and shows the digital ticket in addition to the queue position. The user interface (UI) is made simple and easy to use for the user by having the ticket and status board seem like their real-world equivalents, as shown in Figure 2 below.

While subsection B elaborates on the streaming and queue management unit, subsection A describes the registration and verification unit and the system's workflow [6].An Approach for Non-Critical Service Queue

Management Systems.

The method helps systems that provide non-critical services organize their movables effectively. It also controls the queue of guests arriving. The strategy is to improve the client experience while retaining the advantages of the handed service. A mobile application that displays available times and locations can be used by the customer to schedule an appointment online in the first step. The customer verifies her reservation in the alternative step when she arrives at the service location. She can do this by using a mobile device to scan a QR code. This is essential if you want to avoid touching any screens during the COVID-19 pandemic. The system will decide the class of the client precedence in the third phase. The system will locate the client's position in the virtual line in the fourth phase. Eventually, in the fifth step, the anticipated waiting time to be served is reckoned. Section IV describes the steps leading from 3 to 5. On the mobile operation, the client's position and the remaining time will be reported, allowing her to stay put and return when her turn is about to occur. Managing the line is an essential part of thethus mentioned approach. As a result, Section IV provides a thorough explanation of the precedence line method. Section V applies the strategy and evaluates it [7].

The impact of queuing algorithms on the quality of service for real-time traffic during load balancing

On the connection point of the switch, the components to prevent overburden (line length limits) implement a method of disposing of traffic parcels by extending the normal length of the line, whereas the blockage board is the executives of traffic bundles ready to be upgraded in equipment or programming lines. On the connection point of the switch, the components to prevent overburden (line length limits) implement a method of disposing of traffic parcels by extending the normal length of the line, whereas the blockage board is the executives of traffic bundles ready to be upgraded in equipment or programming lines [8].

Analysis of the queue discipline for the wireless sensor node's dynamic power management.

The line discipline in the context of administrative time is challenging to fictionalize. The line postpones example in this study was completed using the Simulink (MATLAB) environment. Think about a sensor hub that employs the M/M/1 line structure and could recognize and respond to two distinct types of events that show up in its feedback. It has a power supervisor block for controlling the board dynamic power, an occasion age block for creating two distinct types of occasions, a single server for connecting with the sensor hub processor, and a lining defer analyzer for reviewing high and low-need event postponement. The lined defers analysis evaluates the postponement of low- and high-need circumstances using the DPM-based WSN model. When the more essential events are handled first, the executive solution, which employs a remote sensor hub, uses less power and misses fewer occurrences. The high appearance speed of lowneed occasions and low appearance pace of high-need occasions are accepted through demonstration and investigation. If the managing or correspondence of the current development hinders the emergence of a higher need occasion, it is a preventive need strategy rather than a preplanner need strategy. If necessary, the acquired occasions might be returned to the need line for additional treatment to slow down the speed of low-need occasions. The reproduction boundaries for deferred examination are displayed in the image below [9].

CONCLUSION

In this research, a Savvy Line the Executives Framework that can be used for thorough patient administration in emergency clinics is introduced. The Satellite Organization Creator Given that the traffic forecast has an increased cubic capacity, the model is improved with triple dramaticsmoothing, and the executive calculation proposes a better ARED calculation while taking organization traffic expectations into account. The model also includes individual counting, and Line expectation is completed with the use of convolution calculations, sophisticated neural network techniques, and DNN calculations. To sum up, the executive framework brilliant line can increase efficiency and client satisfaction while reducing hanging tight time for administrations.

REFERENCES

[1] "Mobile-Augmented Smart Queue Management System for Hospital"2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS), by S. Soman, S. Rai, P. Ranjan, A. S. Cheema, and P. K. Srivastava.

[2] Y. Bie, Z. Li, Z. Hum, and J. Chen, "Queue Management Algorithm for Satellite Networks Based on Traffic Prediction" in IEEE Access, vol. 10, pp. 54313-54324, 2022.

[3] "Smart Queue Management System with Real Time Tracking Using DNN", International Journal of Emerging Technologies and Innovative Research (www.jetir.org | UGC and ISSN Approved), ISSN:2349-5162, Vol.7, Issue 5, page no. pp135-144, May-2020.

[4] K. W. Tan, H. C. Lau, and F. C. Y. Lee, "Improving patient length-of-stay in the emergency department through dynamic queue management"; 2013 Winter Simulations Conference (WSC),2013.

[5] Q. Xu, G. Ma, K. Ding, and B. Xu, & A"n Adaptive Active Queue Management Based on Model Predictive Control," in IEEE Access, vol. 8, pp. 174489-174494, 2020.

[6] Ghazal, Mohammed, Rania Hamouda and Samr Ali. "A Smart Mobile System for the Real-Time Tracking and Management of Service Queues. International Journal of Computing and Digital Systems 05 (2016).

[7] An Approach for Queue Management Systems of NonCritical Services, 7th International Conference on Information Management (ICIM), 2021, M. Abuser, M. Sharaf, T. Hamad, R.Dahman, and S. Abu Odeh.

[8] "The Effects of Queueing Algorithms on QoS for Real- Time Traffic in Process of Load Balancing" 2018 International Scientific-Practical Conference Problems of Infocommunications. Science and Technology (PIC S&T), by A. Proskochylo, M. Zriakhov, and A. Akulynichev.

[9] A. Pugh and V. Sharma, "Queue discipline analysis for dynamic power management in a wireless sensor node"; 2015 Annual IEEE India Conference (INDICON), 2015.

Development of a Computerized Diagnostic System for Brain MRI Tumor Scanning Using a Robust Information Clustering Technique

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A B S T R A C T

This paper presents the development of a computerized diagnostic system for brain MRI tumor scanning using a robust information clustering technique. The method used for this study is data collection, data processing, feature extraction, artificial neural network, activation function, training algorithm, and classification. The method was modelled using a structural approach that developed the Artificial Neural Network (ANN) algorithm, using tansig activation function and back-propagation training algorithm. The brain tumor detection algorithm developed was implemented with MATLAB Simulink application, and tested with Mean Square Error (MSE) and Regression (R) analysis. The result showed that the MSE is 0.002488 and the Regression result is 0.9933. The algorithm was also comparatively compared with an existing system and the result showed that the new system achieved better regression performance than the others. Then it was deployed as a clinical decision system for the diagnosis of brain tumors and tested, the result showed that it was able to detect patients with brain MRI data.

Keywords Back-Propagation, Magnetic Resonance Imaging (MRI), Neural Network, Simulink, Tansig.

INTRODUCTION

Brain tumors consist of abnormal growing tissues in the brain, resulting from the uncontrolled multiplication of cells [1]. This tumor not only increases the pressure and size in the brain but also causes abnormal neurological challenges. According to the National Brain Tumor Foundation (NBTF), over 300% of all people suffering from brain tumors died in developed countries. If such a mortality rate was recorded for the advanced part of the world, with the best medical facilities so far today, one will then question the devastating effect this epidemic cell has caused in developing and underdeveloped countries [2].

According to [3], Brain tumors are classified into two categories which are metastatic and primary brain tumors. In primary tumors, the cells are originally brain cells, but in metastatic tumors, the cells have already grown and spread into the brain from another infected area of the body. Examples of metastatic brain tumors are glioblastoma, gliomas, pituitary adenoma, acoustic neuroma, and haemangioblastoma among others [4].

Recently gliomas have gained lots of research attention with the main focus due to their increase in cases over the past decade [5]. Consequently, various approaches such as biopsy, spinal tap, MRI scan, neurologic exams, and angiogram have been applied to help solve this problem and diagnose the tumor, however, the main challenge is early detection of this tumor before they get to a certain stage [6].

When this tumor is detected early and treated, the probability of one surviving is so high compared to the reverse. The method of detection involves data collection approaches such as Magnetic Resonance Imaging (MRI), and computer thermograph imaging among others [7]. Among these techniques, the MRI is among the standard techniques used for data collection via radiology machines. This MRI is a non-invasive Vivo imaging approach that employs radio frequency signals to excite target tissues to produce an internal image view under the influence advanced magnetic field [8]. During this scan, information about the various modalities in the brain cell is revealed which are employed for the segmentation of tumors by the radiologist. However, many a time, when the tumor is young, they are not detected by the radiologist due to human error and this has remained a very big problem. This is due to their ability to detect is fully dependent on what the human eye can see at the time of the scan result. However, when the tumor is young, they are almost invisible to the human eyes from scan result as the attributes of an MRI result for a brain tumor vary based on size, and shape, among other characteristics [9].

The use of artificial intelligence techniques and image processing has been proposed by [1] [10] [11] [8] for the development of an automated brain tumor diagnostic system and achieved better results when compared to human experts many a time. From the techniques, the use of machine learning has achieved better results, with an algorithm such as K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and Artificial Neural Network (ANN) among others [12]. But so far, the artificial neural network achieved better recognition accuracy when compared to the rest algorithms.

ANN is a biologically inspired neuron that can learn and make accurate decisions when trained with data. This algorithm will be adopted in this research to develop a clinical decision system for the system [13]. This, when achieved, will help provide an easy-to-use, reliable, and cost-effective system that can be deployed at health centers can facilitate early detection of brain tumors in both rural and urban communities. In many rural localities today in Africa, the average person cannot afford the cost of medical care due to economic reasons (poverty) and the high cost of modern hospital treatments. Health centers are provided in most of these regions as an alternative to hospitals for easy access, but these medical centers lack facilities to diagnose brain tumors due to the high cost of the diagnosis machine, others that have the diagnostic system lack integrity as they are not developed with data collected from Nigerian hospitals. These problems have resulted in the late detection of brain tumors in African communities and the figures keep rising according to the World Health Organization (WHO) every year (2018). Other problems are the issues of human error from radiologists during the analysis of brain tumor data. All these issues have remained a major problem that needs urgent attention and will be addressed in this research using artificial intelligence techniques.

It has been established that brain tumor presents a very complex problem irrespective of the method used to perform the analysis. Many techniques such as deep learning using convolutional neural networks, image processing with segmentation, and fuzzy logic techniques among others have been used to solve this problem over time. However, despite the success, a solution has not been obtained using data collected from Nigerian hospitals for the intelligent diagnosis of brain tumors.

This research is focused on developing a metastatic-based brain tumor detection system using artificial intelligence techniques with the following set out objectives:

- To study the characteristics of brain tumors via data collection.
- To develop a brain tumor detection algorithm using an artificial neural network.
- To implement the algorithm developed with Simulink/Mathlab.
- To evaluate the performance, validate the results, and comparatively analyze the algorithm with the existing system.

MATERIALS

- 0.3T MRI system
- Laptop
- Inverter system
- Rs232 Serial Converter cord
- DICOM Software, etc

The DICOM software which enabled access to patient MRI imagery was installed on the laptop and then connected to the MRI machine using the serial converter cord. The inverter system was used to power the setup for a reliable power supply, and then the MRI data scanned from the test patients were collected.

Method

The method used for the system development is data collection, data processing, feature extraction, artificial neural network, activation function, training algorithm, and classification.

The data used for the study was collected from Memfy's Hospital Enugu as the primary source of data collection. The sample size of data provided by the hospital is the MRI data of 25 patients under the age of 45 with brain tumor cases where each patient provided 15 samples. The secondary source of data collection was the kaggle repository which provided 4,240 sample MRI data with the total sample size of data collected and used as the training dataset being 4615 MRI data with a brain tumor. The samples of the data collected are shown in Figure 1, while the attributes are in Table 1.

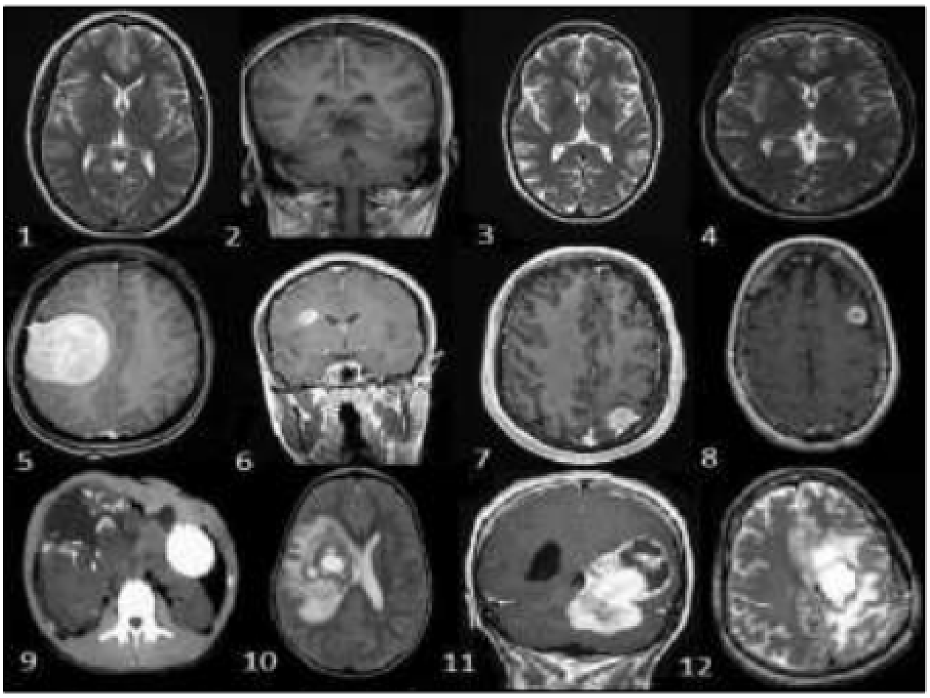

Figure 1. Data sample of brain MRI scan

Figure 1 presented the MRI sample data of the brain scan with the attributes of the brain tumor presented in Table 1.

Table 1. Attributes of Brain Scan [14]

S/N	Attributes
1	Medulloblastoma
2	Memimgioma
3	Pituitary
4	Low-grade Astrocytoma
5	Malignant astrocytoma
6	Malignant glioma
7	Ependymoma
8	Mixed glioma
9	Ganglioglioma
10	Choroid plexus tumor
11	Suprasellar
12	Craniopharyngioma
13	Germ cell tumor
14	Hypothalamic

Data processing

This process involves the removal of noise from the data collection for reliability. The data processing was done using the Gaussian filter model which removed the excess frequency which has the potential to dent the feature of the MRI scan before processing.

Data Extraction

This process was used to drill the MRI data from the scanned result into a statistically compact feature vector. The extraction process was done using a static and dynamic approach as given in [15]. This process was used to drill the data and extract the feature for training using the artificial neural network model developed in the next section.Brain Tumor Detection AlgorithmTo develop the brain tumor algorithm, the model of the feed-forward neural network in [16] was adopted and sued to develop the algorithm. The artificial neural network model was developed using a single neuron and activation function and then interconnect to form the neural network model based on the attributes of the brain tumor data characteristics as given in Table 1. The model of the neural network was presented in Figure 2.

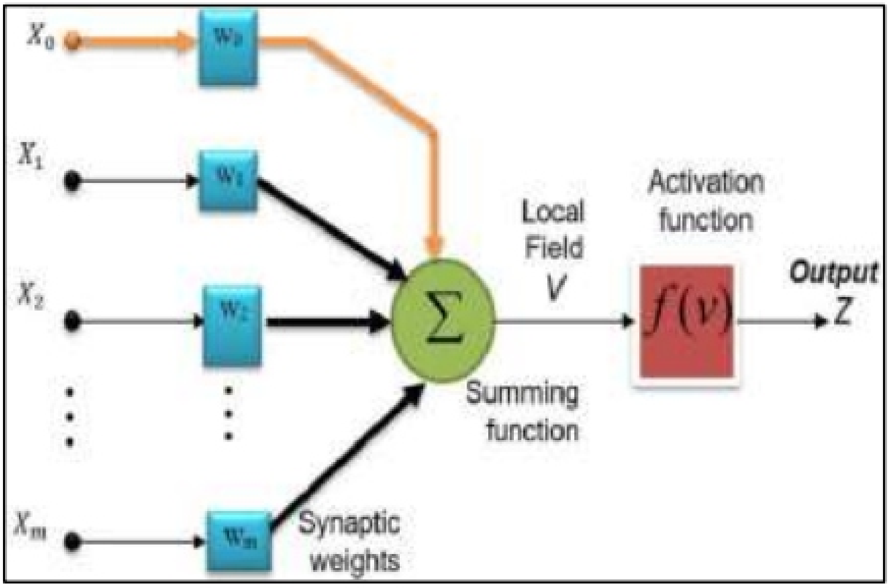

Figure 2. Model of a Single Neural Network

Figure 2 presented the model of a single neural network developed with neurons (X) which have weight (w), and summed and activated with the f(v) activation function to produce the output Z. The choice of activation function used is the tansig activation function as it does not explode during training unlike the sigmoid function and also does not have issues of convergence during training. The neural network model was reconfigured with the training parameters in Table 2 to form the neural network model used for training the brain tumor data collected.

Table 2. Neural Network parameters

Parameters	Values
Epoch	100
Epoch between display	10
Maximum time to train in sec	Infinity
Maximum validation failure	5
Number of hidden layers	3
Momentum factor	0.75
Learning rate	0.01
Minimum performance gradient	1e-6
Number of input neurons	14
Weight of neurons	14

Table 2 was used to develop the neural network model as shown in Figure 3 with the input layers, hidden layers, and output layer. The hidden layers are the section of the neural network where the computation process was done using the training algorithm. The activated neurons from the input are processed in the hidden layer using the training algorithm to learn the neurons of the brain tumor attributes until the least mean square error is achieved and the algorithm develops.

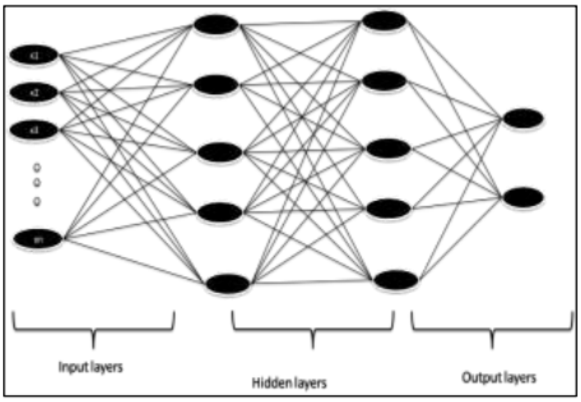

Figure 3. Model of the neural network architecture

Figure 3 presented the model of the neural network used to train the data collected from the sampled patients. The block diagram of the training process was presented in Figure 4.

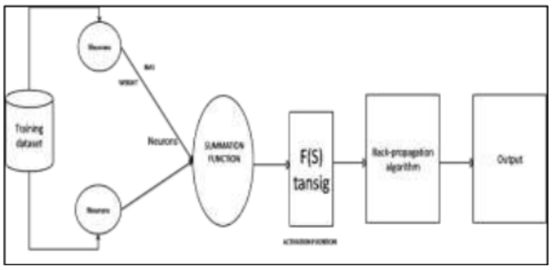

Figure 4. Model of the Neural Network Training

The neural network model block shown in Figure 4 was used to train the data collected to generate the brain tumor algorithm as the output. The training algorithm used is the back-propagation algorithm adopted from [1] and used to train the data and the generated brain tumor time series classification algorithm is presented in the pseudocode below:

1. Start
2. Load brain tumor data
3. Initialize activation function
4. Initialize training algorithm
5. Initialize epoch values and intervals
6. Configure the neural network model as in
Figure 3.3
7. Train neural network with Figure 3.4
8. Check for the Least Mean Square Error (MSE)
9. If
10. MSE ≈ 0 Then
11. Generate the reference brain tumor algorithm
12. Else
13. Back-propagate and adjust the weight
14. Return to step (8)
15. Apply step (11)
16. End

The system flow chart:

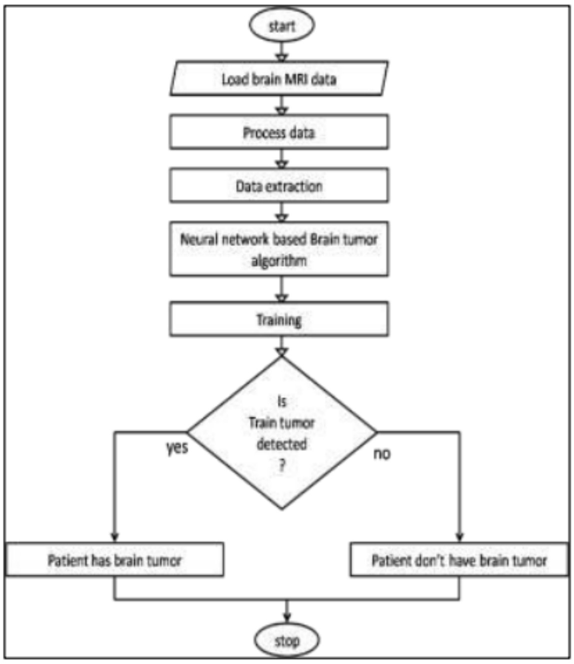

Figure 5. Brain Tumor Detection System flow chart

Figure 5 presents the brain tumor detection logical flow chart showing how the algorithm was used to develop the brain tumor detection system. The figure showed how data input from the MRI scan was loaded into it for processing with the Gaussian filter adopted and feature extraction method adopted too. The algorithm developed was then used to classify the check for a brain tumor and make intelligent decisions. The system developed was implemented in the next section.

SYSTEM IMPLEMENTATION

The system developed was implemented with a database toolbox, neural network toolbox, statistic and machine learning toolbox, and data processing toolbox in Simulink. The neural network toolbox was configured with the algorithm developed. The feature extraction toolbox was used to configure the statistics and machine learning toolbox, the Gaussian filter was used to configure the data processing toolbox. Then all the toolboxes were integrated into Simulink to develop the new system.

Figure 6 presented the neural network toolbox used to develop the new system. The tool showed the four items labeled a,b,c, and d. Before the training begins, the neural network divides the data into training, test, and validation sets in the ratio of 70:15:15; (a) presented the input neural network model configured when the brain tumor data was loaded for training. The (b) presented the back-propagation process which took place during the training process to adjust the neurons until the best version of the brain tumor classification algorithm was generated. The (c) was used to show how the training set was tested with the test set to make classification before the result was achieved. (d) Shows the training tool which was also used to evaluate the performance of the algorithm with regression and MSE.

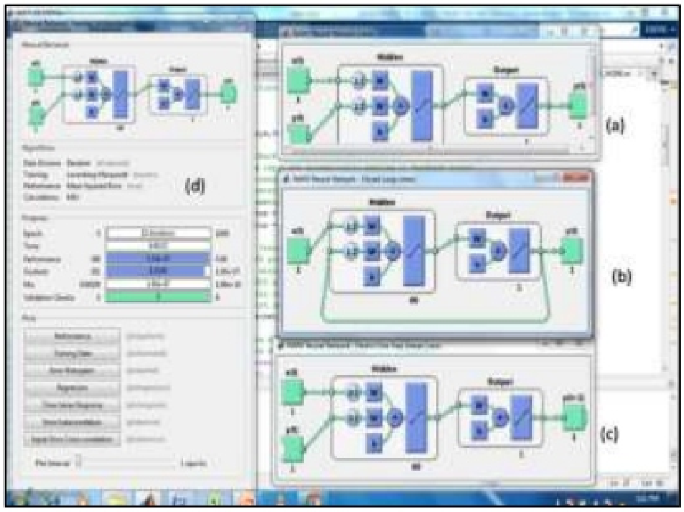

Figure 6. The Neural Network Toolbox

RESULTS OF NEURAL NETWORK TRAINING

This section presents the performance of the neural network algorithm developed. The result used MSE and regression to measure the performance of the algorithm to check the error recorded during the process and also the relationship between the true and false positive rate using a regression analyzer. The MSE result of the neural network was presented in Figure 7.

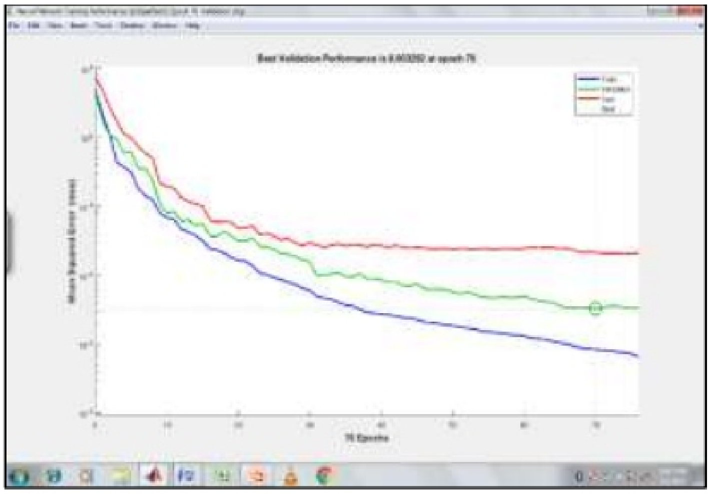

Figure 7. The MSE Performance.

Figure 7 presented the MSE performance of the brain tumor detection algorithm developed. From the result, it was observed that the MSE result is 0.003292Mu at epoch 70.

This implication of the result showed that the error achieved in the training of the algorithm is approximately zero and hence acceptable with an indication that the least error was recorded during the training process. The Regression performance was also presented in Figure 8.

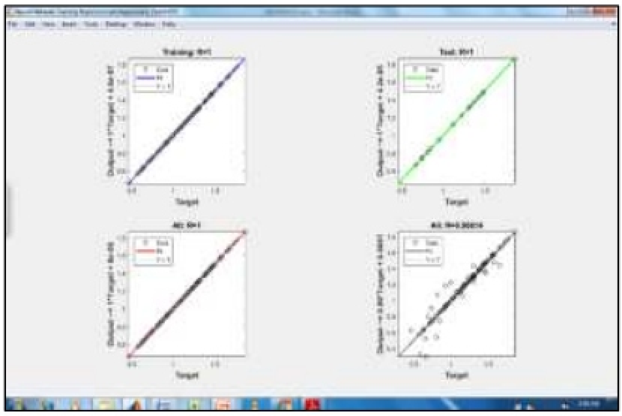

Figure 8. The Regression Performance.

From Figure 8 the regression result presented the performance of the algorithm in detecting brain tumors. The result first showed that during the training process that fitting was not achieved, thanks to the activation function used. The regression was measured using the average of the training, test, and validation sets to record the regression of the algorithm as R=0.96614. This result implied that the performance of the algorithm to detect brain tumors is very good as it is approximately equal to the ideal regression value of 1.

Validation of the Algorithm Result

The algorithm validation was done using a tenfold crossvalidation technique which measured the performance of the brain tumor detection algorithm tenfold and then compute the average using MSE and Regression as presented in Table 4.

Table 4. Validation result of the filter with GDA

S/N	MSE (Mu)	Regression
1	0.003292	0.9954
2	0.003254	0.9976
3	0.003155	0.9951
4	0.003358	0.9968
5	0.002373	0.9939
6	0.002415	0.9953
7	0.001752	0.9920
8	0.002173	0.9942
9	0.003214	0.9972
10	0.003451	0.9988
Average	0.002488	0.9933

Table 4 presented the system validation performance using MSE and Regression, the average result showed that the MSE is 0.002488 and the Regression result is 0.9933.

System Integration as a Brain Tumor Detection System

After the development of the proposed system, tested, and validated the algorithm; it was integrated as a clinical decision system using MATLAB software as shown in Figure 9.

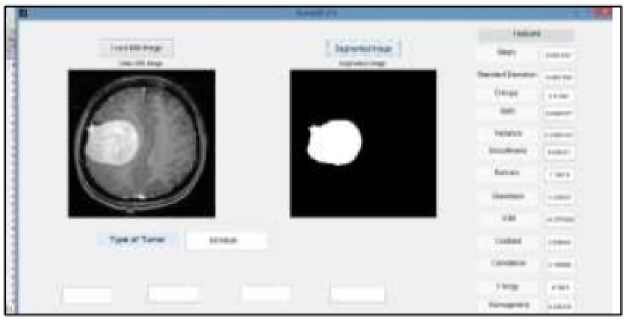

Figure 9. The system results

Figure 9 presented the brain tumor detection system with the MRI upload which was processed with the Gaussian filter to segment the segment of the cell and identify and reveal key parts of the MRI for a better feature extraction process in Figure 10.

Figure 10. Brain MRI diagnosis for tumour

Figure 10 presented the result of the feature extraction process which was used to drill the important features of the brain tumor attributes and then classified with the algorithm developed to detect brain tumors as shown in Figure 11.

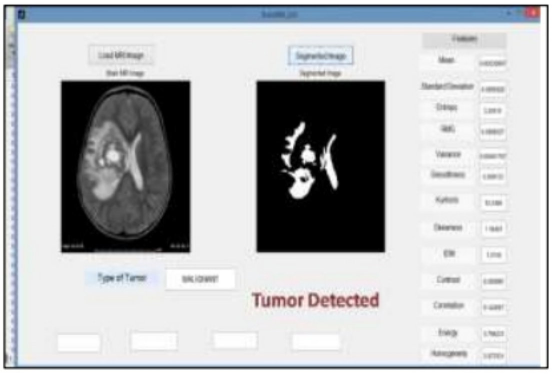

Figure 11. Brain MRI diagnosis Result

Figure 11 showed how the algorithm was used to classify the features of the input MRI data to detect tumor problems in the patient. The next result also showed the system performance when used to test for a patient without a brain tumor and the result was presented in Figure 12.

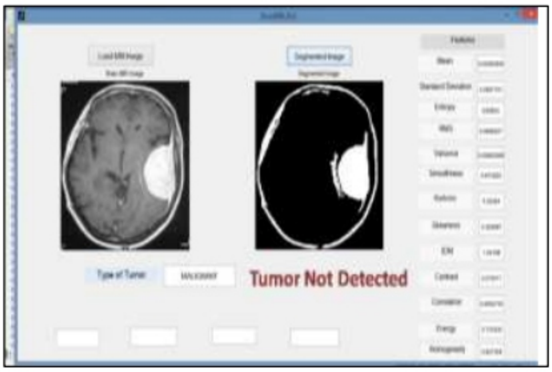

Figure 12. Bain MRI diagnosis for malignant tumour

CONCLUSION

The study has successfully developed an expert system for the diagnosis of brain tumors using an artificial neural network. This was achieved via data collection of MRIpatients below 45 years and then used to develop a brain tumor detection algorithm. The algorithm was integrated as a clinical decision system and then tested with regression and MSE. The result showed that the MSE is 0.002488 and the Regression result is 0.9933. The performance was compared with the existing state-of-the-art algorithms and then the result showed that the new system performed better. The performance was also compared with the existing algorithm developed recently and the result showed that the new algorithm achieved better regression performance when compared to the rest.

REFERENCES

[1] Naveena H., Shreedhara K., Mohamed R., (2015). Detection and Classification of Brain Tumor using BPN and PNN Artificial Neural Network Algorithms, International Journal of Computer Science and Mobile Computing,

[2] National Brain Tumor Foundation (NBTF), 2019.

[3] Yazdani S., Yusof R., Karimian A., Pashna M., Hematian A., (2015). Image segmentation methods and applications in MRI brain images. IETE Tech. Rev. 2015;32(6):413–27. https://doi.org/10.1080/02564602.2015.1027307.

[4] Jayadevappa D., Kumar S., Murty D., (2011). Medical Image Segmentation Algorithms Using Deformable Models: A Review. IETE Tech. Rev. 2011;28(3):248–55. https://doi.org/10.4103/0256-4602.81244

[5] Abd-Ellah M., Awad A., Khalaf A., Hamed H., (2016). Classification of Brain Tumor MRIs Using a Kernel Support Vector Machine. Building Sustainable Health Ecosystems: 6th International Conference on Well-Being in the Information Society, WIS 2016, CCIS vol. 636. 2016. p. 151–60. https://doi.org/10.1007/978-3-319-44672-1_13.

[6] Vijay K., & Raju G., (2018). Biological Early Brain Cancer Detection Using Artificial Neural Network. International Journal on Computer Science and Engineering, Vol. 02

[7] Liu J., Li M., Wang J., Wu F., Liu T., (2019). A survey of MRI-based brain tumor segmentation methods. Tsinghua Sci. Technol. 2019;19(6):578–95. https://doi.org/10.1109/TST.2014.6961028.

[8] Işin A., Direkoğlu C., Şah M., (2016). Review of MRI-Based Brain Tumor Image Segmentation Using Deep Learning Methods. Proc. Comput. Sci. 2016;102(Supplement C), 317–24. https://doi.org/10.1016/j.procs.2016.09.407 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29- 30 August 2016, Vienna, Austria.

[9] Gordillo N., Montseny E., Sobrevilla P., (2013). State of the art survey on MRI Brain Tumor Segmentation. Magn. Reson. Imaging 2013, 31(8), 1426–38.

[10] Lugina M., Retno N., Rita R., (2016). Brain Tumor Detection and Classification in Magnetic Resonance Imaging (MRI) using Region Growing, Fuzzy Symmetric Measure, and Artificial Neural Network Backpropagation, International Journal of Science and Research, 2016.

[11] Virupakshappa, & Basavaraj A., (2018). Computer Based Diagnosis System for Tumor Detection &Classification: A Hybrid Approach, International Journal of Pure and Applied

[12] Danda S., Chinta N., Carmel M., (2018). Brain Tumor Prediction Using Naïve Bayes Classifier and Decision Tree Algorithms. International Journal of Engineering and Technology.

[13] Dena N., Hashem B., AnwerSubhi A., (2015). Brain Tumor Detection Using Shape Features and Machine Learning Algorithms. International Journal of Scientific & Engineering Research, volume 6, issue 12.

[14] Monica S., Sarat K., (2019). Brain MR Image Segmentation for Tumor Detection using Artificial Neural Networks", International Journal of Engineering and Technology (IJET), Vol. 5, No 2, Apr-May 2019.

[15] Nikita S., Naveen C., (2018). Classification of Brain Tumor Types Using Multiclass Kernel-Based Hellinger Decision Method for HD-tree and HD-forest", International Journal of Engineering and Technology.

[16] Sankari S., & Vigneshwari., (2017). Automatic Tumor Segmentation Using Convolutional Neural Networks. Third International Conference on Science Technology Engineering and Management (ICONSTEM)

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