Learning to Predict Dental Caries for Preschool Children

SANGHVI N , SARATH J V , SATHISH K , KAVIN D

DEPARTMENT OF COMPUTER SCIENCE ANDENGINEERING AND ARTIFICIAL INTELLIGENCE AND DATA SCIENCE BANNARI AMMAN INSTITUTE OF TECHNOLOGY

1. INTRODUCTION

Dental diseases (dental caries, periodontal disease, dental fluorosis, etc.) have become more common. Even with a good understanding of dentistry, problems can occur with almost any tooth. A new oral health study shows that 94% of the Chinese population suffers from a variety of dental problems, worryingly. However, in most cases, dental diseases can be prevented and serious problems can be avoided if the teeth are regularly cared for. In addition, the follow-up of diseases in the body, gingiva and oral mucosa, cardiovascular and cerebrovascular diseases, diabetes, AIDS, etc. It can play an important role in the follow-up of patients with problems. The concept of the Internet of Things, which is increasingly popular today, has influenced every aspect of human life. In particular, IOT-based health services are used in many areas, thus providing a variety of treatments. Treatment can be improved, as can early detection and prognosis. But with the advent of IoT-based healthcare, smart Home Centric dentistry solutions can be developed to become a true pre-treatment. While these studies mainly focus on IOT-based healthcare platforms, there are also some studies on home dentistry and services.

2. DESCRIPTION:

Internet of Things (IOT) has become a business, its applications ranging from agriculture to healthcare to transportation. The hospital environment can be very stressful, especially for the elderly and children. As the world population continues to increase, doctor-patient appointments are becoming less and less effective. That's why smart treatment is so important. Smart healthcare can be used at any level, from taking a child's temperature to monitoring an adult's vitals. The complexity and cost of use will vary depending on the precision and functionality required for each product and the complexity of the application used. Smart healthcare is also in verticals such as massive integration, connected systems, big data, machine learning, cloud computing and artificial intelligence. This article discusses the importance, needs and applications of smart healthcare, as well as the current market and products. It provides a deeper understanding of the different platforms, leading to more research in this dynamic area

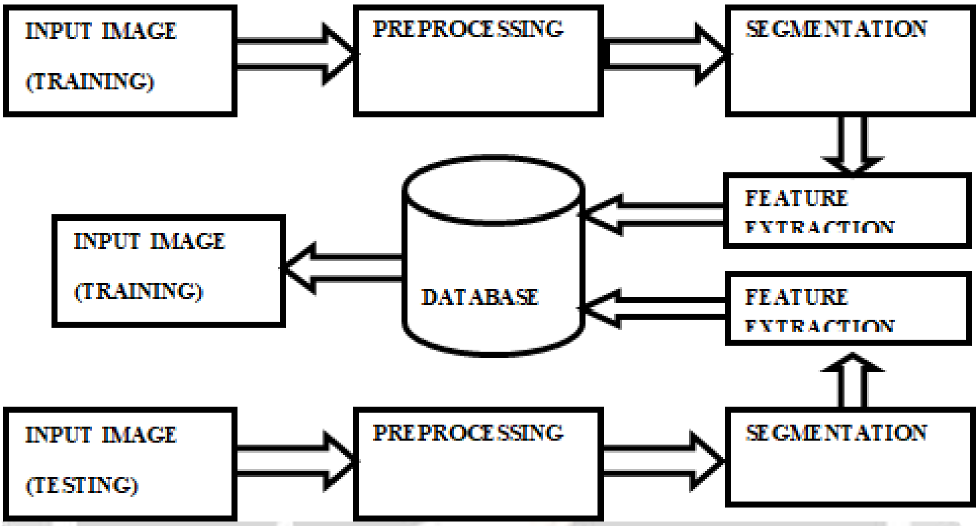
3. EXISTING SYSTEMS

In current systems, support vector machines are used to identify dental diseases. But for the purpose of the decision, for the sake of, for the sake, for the sake, for the sake, for the sake, for the sake, for the sake, for the sake, for the sake - the process of automatic support, including conversion and support vector machines for dental disease prediction. The proposed segmentation uses adaptive thresholding to segment important data to extract features from the input images. Adaptive thresholding is determined by pixel probabilities and variances. In the feature extraction step, fragmented regions will be used to extract features that describe the color and texture content. Color features were extracted from the HSV color space of selected regions based on histogram analysis. Assign colors and textures to the SVM training and use the model for classification. SVM (Support Vector Machine) is a supervised learning model used to carefully classify and define tooth images as normal or abnormal based on their radial basis kernel functions. The SVM training phase consists of training the SVM with the desired features and related results. Perform a similar subtraction to train the SVM with features. Second, the SVM classifier stage represents the decision process in which the features of the training model are compared with the input image. Use the "svm train" command to train the SVM using the required inputs and outputs. Here, Goal 1 under normal conditions and Goal 2 in all abnormal situations are considered desirable results. After training, the new training set and different parameters in the network are stored for input and simulation. In the classification phase, the test image is used to supplement the training model with the SVM model using the "SVM Classify" command. The tooth images entered according to this command are classified. Therefore, the defects related to the input image are analyzed for future studies.

4. MANUFACTURING PROCESS

proposes to build a neural network based on the classification of dental diseases. Oral health refers to the presence and absence/healing of caries. The approach is to build artificial intelligence equipment (Ann) as a computer diagnostic tool and find general patterns of patterns that allow for the classification of subjects. Classification model according to validity statistical analysis, statistical accuracy, loss function, receiver operating characteristic (ROC) curve and area under the curve (AUC) no.

5. BLOCK DIAGRAM:



6. COLOR FEATURE EXTRACTION

Color space represents the color in the form of intensity value. We can specify, visualize and create the color by using color space method. There are different color feature extraction methods. Color feature extraction methods: a. Histogram Intersection Method: Histogram Intersection (HI) considers global color Features. The color histograms X and Y with k bins for each, HI is defined as, In Histogram Intersection method, the number of bins makes impact on performance. The large no of bins represent the image in very complex manner it increases the computational complexity.

The Grey Level Co occurrence Matrix Is Statistical approach. Texture features are calculated from the statistical distribution. This method is a technique of extracting subsequent order statistical texture features. The elements of matrix represent the relative frequency. This method describes texture by creating statistics of the dispersal of intensity values as well as location and orientation of similar valued pixel.

1. Maximum probability entry

2. Element difference moment of order k: PiPj (i−j)kcij This descriptor has relatively low values when the high values of Care near the main diagonal. For this position operator, high values near the main diagonal would indicate that bands of constant intensity running “1 pixel to the right and 1 down” are likely . When k= 2 , it is called the contrast

$$Energy = \sum_{i,j=0}^{N-1} \left(P_{ij}\right)^2$$

$$Entropy = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right)P_{ij}$$

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}\left(i-j\right)^2$$

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+\left(i-j\right)^2}$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

$$Shade = \operatorname{sgn}\left(A\right)\left|A\right|^{1/3}$$

P_{ij} = Element i,j of the normalized symmetrical GLCM

N = Number of gray levels in the image as specified by Number of levels in under Quantization on the GLCM texture page of the Variable Properties dialog box.

μ = the GLCM mean (being an estimate of the intensity of all pixels in the relationships that contributed to the GLCM), calculated as:

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$$

σ^2 = the variance of the intensities of all reference pixels in the relationships that contributed to the GLCM, calculated as:

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2$$

This may approximate, but is not identical to, the variance of the intensities of all the pixels in the data window W (as defined by the GLCM algorithm), and it is dependent upon the choice of spatial relationship in that algorithm.

C = The Correlation feature

sgn(x) = Sign of a real number

x = -1 for x < 0 x = 0 for x = 0 x = 1 for x > 0

$$\sum_{i,j=0}^{N-1} \frac{(i+j-2\mu)^4 P_{ij}}{4\sigma^4(1+C)^2}$$

7. CONFUSION MATRIX

A similar matrix can be made for a multi-class classifier. The numbers of right and wrong classifications are gathered in their respective slots in the matrix:

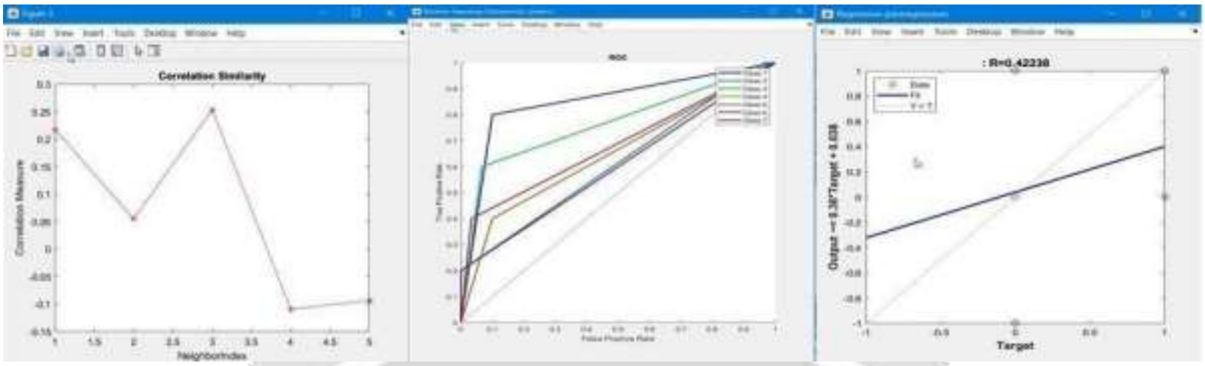
TP = number of true positives, FP = false positives,
FN = false negatives, TN = true negatives.
Total number of test set samples = (TP+FP+FN+TN).

General "accuracy" = (TP+TN) / (TP+FP+FN+TN). "Sensitivity" = TP / (TP+FN). Specificity= TN / (TN+FP)

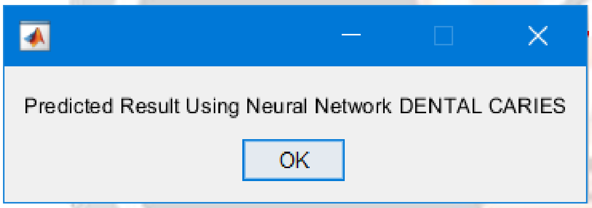
8. RESULT AND DISCUSSION:–

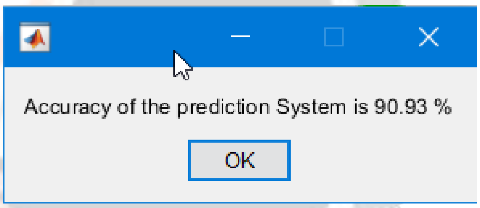
Unit	Initial Value	Stopped Value	Target Value
Epoch	0	7	10
Elapsed Time	-	00:00:03	-
Performance	0.394	0.0272	0
Gradient	0.613	0.0358	1e-07
Mu	0.001	0.0001	1e+10
Validation Checks	0	6	6

Prediction (full-blown) has the greatest accuracy overall, followed by prediction (screening). The community at large screening paradigm ultimately performs the lowest. Such findings demonstrate the greater importance of high-cost characteristics like oral examination (clinical examination as in the table) and biologic testing. An important factor in the outcomes. In addition, we discover that linear learning models such both Linear Discriminant Analysis and Logistic Regression perform comparably better than a nonlinear model. Our hypothesis is that a high dimensional classification algorithm, such as SVM with a Gaussian kernel, will readily overfit the data set. The most accurate categorization is based on LDA, which has a classification error of 14.15%.



We can observe from the ROC curve that SVM (linear kennel), LDA, and Logistics Regression are well ahead of SVM (polynomial) and SVM (rbf Gaussian) in Prediction (Full-Blown) and Prediction (Screening). The benefit, however, decreases when the characteristics from the oral examination and biologic testing are removed from the community-screening model. The oral examination and biologic tests relate more directly to the result of caries, which is why an incorrect feature space will distort the efficacy of effective learning algorithms.





Result 1 Result 2

9. CONCLUSION

This paper proposes an iHome smart dental Health-IoT system based on intelligent hardware, deep learning and mobile terminal, aiming to regulate as well as optimize the accessibility of dental treatment and provide home-based dental health care service more efficiently. The trained model was used to realize the detection and classication of dental diseases, and application software (Apps) on mobile terminal was designed for client-side and dentist-side. The software platform with the functions including pre-examination of dental disease, consultation, appointment, and evaluation, etc, made the service docking between the patient and the dentist resources a reality. The AI algorithm achieved more than 90% recognition rate for seven dental diseases, which has greatly improved the patient rate and the resource utilization rate of the dental clinic and it showing high reliability in practical application.

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