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MEDICAL DECISION SUPPORT SYSTEM FOR BRAIN IMAGE CLASSIFICATION

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Abstract. The classification of brain tumors in magnetic resonance imaging (MRI) is very significant for diagnosis and detecting the tumors in the medical world. The major advantages of MRI are soft tissue analysis and non-invasive but the drawback is a long time consumed by a medical expert to draw conclusions. The classification algorithms help in order to overcome the disadvantage of MRI. In this work, brain tumor classification is done based on the GLCM feature values where 165 brain medical images are presented. The main aim of this work is solving the cancer classification by implementing 3 different classifiers such as NB (Naïve Bayes), NN (Neural networks), and SVM RBF (Support vector machine Radial Basis Functions). The features of the images are extracted using GLCM and further, the feature values are classified as either affected or not affected. Among 3 classification approaches, NN achieves superior accuracy (99%) with less error rate.

Keywords: MRI, GLCM, Naïve Bayes, NN, SVM RBF.

Introduction

The benefit of the CAD system can be a dual reading, which can produce competent and resultant factors of reducing errors and aid in rising sensitivity in the image analysis by a radiologist. Magnetic Resonance (MR) imaging is a popular approach that is applied to achieve top quality medical images. It is one of the suitable, painless and non-invasive imaging methods. Specifically for brain MR imaging, reports a different view by implementing top-level spatial and contrast resolution. It is applied for detection of diseases and provides top quality informative images of the body. However, the information extracted from the images is vast, and it is challenging to generate a conclusion based on such basic data. In such events, the authors intend to apply different image analysis tools to evaluate the MR images and extract data to be discriminated into normal or abnormal status of the brain. Recent research work has proven that discrimination of brain in MR images is feasible via machine learning and discrimination methods such as NN and SVM. Recently, interests in applying NN have improved, as of its speed and accuracy. The study has applied machine learning techniques to attain the discrimination of MR images that belongs to two classes, normal and abnormal. In this research work, we have analyzed the performance of three classifiers, such as SVM RBF [1], NN [2] and NB [3].

The naïve Bayes classifier is a classifier that is working with influence of Bayes' theorem. It is one of the classification approach that base on the statistics. It is usually denoted that NB approach are ease to build with no complicate iterative parameter. As the attributes are fully independent for the output class, this classification can easily implement in all research fields [4].

NN: NN is relevant for non-linear problems with good flexibility. Neural networks excel in the supervised method for tissues discrimination into cancerous or non-cancerous naturally. The proposed aim of the study is to decrease the model complexity for MR image discrimination in terms of classification accuracy.

SVMs have committed a considerable deal of attention from the machine learning techniques and due to their exclusive properties, such as great observation achievement, robustness in the existence of noise, capacity to Pledge with large dimensional data, and behavior of neurons can be trained to observe and classify complicated patterns.

The main targets is creating an advanced technique for discrimination of MR brain images using second order statistical features and are classified by NB, NN and SVM RBF. The outcome presents that the

proposed methods are effective and powerful. According to the outcomes, the proposed approach is cabable to generate powerful medical image discrimination.
The rest of the paper is arranged as follows at first literature survey and second materials and methods. Next section deals with feature extraction using second order statistis in brain MR images. In the next stage, the classification techniques (NB, NN and SVM RBF) are engaged for the data processed from feature extraction technique. The classification outputs proved that the neural network (NN) technique has great accuracy (99%). Finally, this work documented and planned the model that is usable and secure for classifying tumor in brain MR images.

Literature survey

Aruna Devi et al., [5] have presented MR image classification by JAFER feature selection and compared the same among five methods, of which ANN BP method provides 98% classification accuracy. Yang et al., [6] proposed a new method using independent elements from MRI measures as well as clinical assessments. Classification is done by SVM classifier and the classification accuracy is 97.7%. Huang et al., [7] presented a classification which is in the fusion of SVM as well as Adaboost. It proves that it worked well, and attained greater classification accuracy than traditional classification like K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA), SVM, as well as Gaussian Mixture Model (GMM). Aruna Devi et al., [8] have proposed GLCM feature extraction, and discriminated tumour by SVM and ELM, and achieved 96% classification accuracy. Padilla et al., [9] proposed a technique for diagnosis of Alzheimer's on the base of Non-negative Matrix factorization (NMF) as well as SVM. The proposed NMF-SVM method achieved classification accuracy of 91%. Portugal et al., [10] proposed the features extraction basis on Gabor Filtering and a classification done by using SVM with different kernels. The author experiments with MRI brain images and achieved a classification accuracy of 95% using SVM RBF method. Aruna Devi et al., [11] applied GLCM features extraction, and discriminated medical images by ANN and SVM classifiers. ANN method obtains 96% of classification accuracy. Lahmiri et al., [12] proposed a method for2D DWT and Gabor wavelet features' extracting from MRI brain images and classification was done by using SVM. The obtained accuracies of MRI brain images, mammograms and retina were 86%, 68% and 50% respectively. Kharrat et al., [13] presented the feature extraction method of GLCM and DWT and discriminated the Brain MR scans by GA and SVM. The author has attained the 97% of accuracy. B.A Devi et al. [14] have presented second order statistical feature extraction and discriminated the pancreas MR images using ANN BP, ELM methods. The author achieved classification accuracy of 96%. Beura et al., [15] proposed the method of DWT feature extraction and F-statistic feature selection and classified by BPNN (back propagation neural network). DWT has drawbacks in capturing related data and a lack of translation-invariant. Bauer et al. [16] proposed a method of feature extraction by first order statistical features. Thus many textures cannot be distinguished using first order statistical features. Gomez et al., [17] proposed a method of GLCM features and discriminated by LDA (Linear Discriminant Analysis). The author achieved the accuracy of 87%. Based on the survey, the classification accuracy of classifiers is less and computational time is high. NB has its simplicity, it outperforms than other refined classification methods [3, 18]. The previous research presented that the NB techniques strongly achieved in the many cases i.e., as a tool for public health surveillance from huge organizational databases, forecasting the medication and complexity for children, and as a tool for detecting the B-Chronic Lymphocytic Leukemia [19, 20, 21].

In this research work, the authors have classified the brain MR images as normal or abnormal by using second order statistical features and classified by three methods such as NB, NN and SVM RBF. Performance measures like classification accuracy, precision and recall are measured and compared among the three methods.
The data applied for estimating the performance of the suggested model in this study are the MR images of brain, which are gathered from Harvard medical school [22]. The total numbers of MRI brain images involved are 165, of which 99 are normal, and 66 are abnormal MR images. The brain MR images have dimension 512*512 and are in the plane of axial. Fig. 1 represents the flowchart. Fig. 2 displays the normal brain MR images and Fig. 3 displays the abnormal brain MR images.

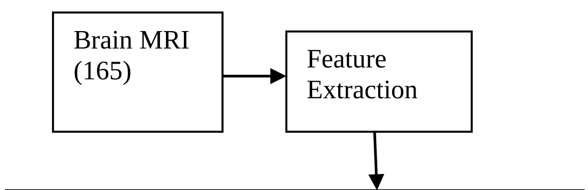

Fig 1.Flow chart

Fig. 1 Flowchart

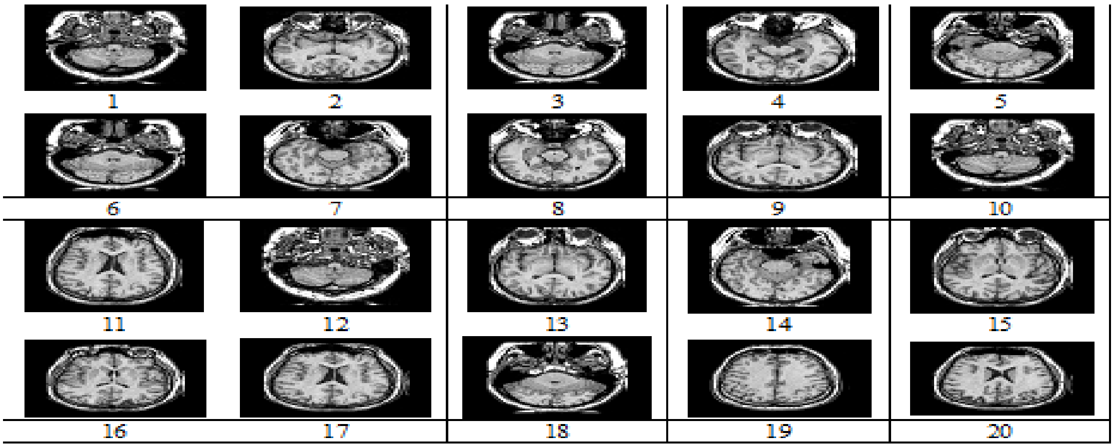

Figure.2 sample normal brain MR images**.**

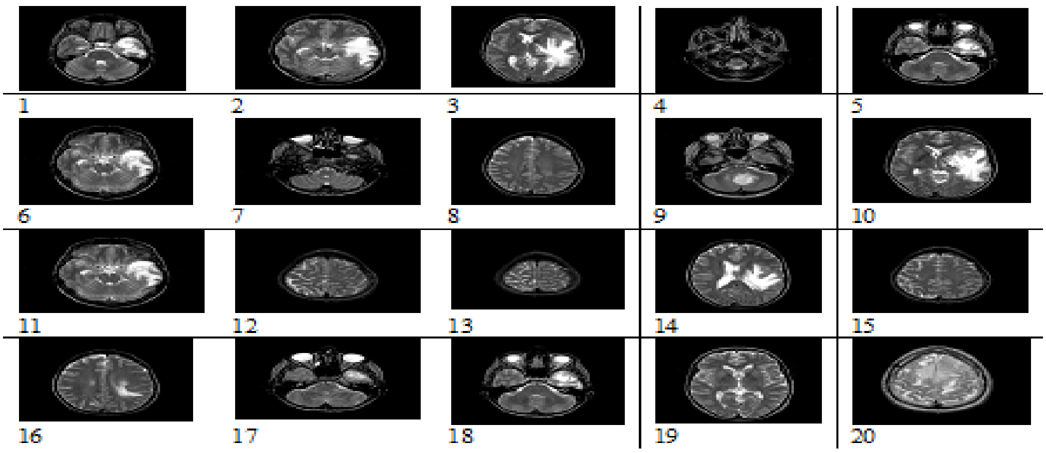

Figure.3 Sample abnormal brain MR images.

GLCM features	Description
Contrast	It measures regional changes among the pixels.$\sum_i \sum_j (i-j)^2 g_{ij}$
Energy	Intensity regularity of an image.$\sum_i \sum_j g_{ij^2}$
Entropy	The disarray and it will have the greatest value while all of the co-occurrence matrices are identical.$\sum_i \sum_j g_{ij} \log_2 g_{ij}$
Homogeneity	The coincidence among the two pixels in an image.$\sum_i \sum_j (1/1+(i-j)^2) g_{ij}$
Cluster prominence	It describes the asymmetry of an image
cluster shade	It is identical to cluster prominence in that it also describes the lack of symmetry in the image.
Sum entropy	The average amount of information required to encode the image values. -$\sum_{i=2}^{2Ng} i\, g_{x+y}(i) \log \{g_{x+y}(i)\}$

Features extraction:
Second order statistical feature extraction: It is one of the image texture quality techniques because it can be resolved efficiently. Second order statistical feature extraction method consists of data around the locations of pixels having identical grey level matters. Second order statistical feature extraction method extracts the basic content around the texture pattern to be evaluated at disparate range and direction. This has made the Second order statistical feature extraction method more active, and more complex. This method discriminates the image by seeing only a pixel pairs. Second order statistical feature extraction method presents a summary of how much disparate pairs of pixels appear in an image. Feature extraction is applied to shorten the dimensionality of an image while extracting all intelligent data from it. The extracted feature vector is applied to brain MR image discrimination. In this work, the second order statistical features like contrast, entropy, energy, cluster shade, cluster prominence, sum of variance, homogeneity, sum of entropy and information measure of correlation are extracted. In this research work, 9-second order features are extracted from each image as explained in Table 1.

Table. 1 GLCM features

Sum variance	$\sum_{i=2}^{2Ng} (i - \mathrm{SUM\ ENT})^2 \cdot g_{x+y}(i)$
Information measure of correlation	It is similar to sum of average which belongs to variance. HXY-HXY1/max{HX,HY}; $(1 - \exp[-2.0(\mathrm{HXY2} - \mathrm{HXY})]^2$

Classification:
The assessments of the preferred features allowing different classes have a significant role in medical analysis. Classifiers support in action of computerized discrimination of features. The major target is the automated classification that is executed to select the excellent classifier.

NB:
Naïve Bayes belongs to the group of conditional probability models; hence it is referred as a probabilistic classifier or statistical classifier [4]. There is a strong independent assumption among the attributes which is said to be conditional independence. Suppose there is an orange fruit that has features of round, orange and around 3 inches of diameter. Even though the corresponding attributes or features are depended on each other, the properties belong to the feature are seems to be Bayes independent to their probability contribution; for that reason the classifier is called 'Naïve'. This algorithm used the formula of Bayes' theorem which is stated as equation 2.

$$p(Y_k|X) = \frac{p(Y_k)\, p(X|Y_k)}{p(X)} \qquad (2)$$

Where $p(Y_k|X)$ refers to the posterior probability,$p(X|Y_k)$ is the likelihood that revealed the evidence given that the hypothesis is correct, $p(Y_k)$ is the prior probability ie., how likely was the hypothesis before identifying the evidence and $p(X)$ acts as a normalizing constant. The benefit of NB classifier is that only fewer amounts of training data are required and easy to implement the algorithm.

NN:
Back Propagation method is one of the powerful techniques applied to train NN. It is applied to feed-forward multilayer networks which contain continuously differentiable activation functions and neurons. Neural networks have layers such as input, output and hidden layers. The activation function of the neuron is the sum of all inputs x_i multiplied by the suitable weights w_{ji} of the neurons.
The output of the neural network is described by the following equation 1:

$$Y = F_o(\sum_{j=0}^{m} w_{oj} \, (F_h \sum_{i=0}^{n} w_{ji} x_i))) \quad (1)$$

where w_{oj} represents the weights in the hidden layer to the single output neuron, Xj represents the ith element of the input vector, F_h and F_o are the activation function of the neurons from the hidden layer and output layer, respectively, w_{ji} is the connection weights between the hidden layer and the inputs.
The dataset that is applied to the input layer may be numerical, and the input layer leads it to the hidden layer. Every neuron which occurs in the hidden layer has a set activation value and dataset from the input layer is applied to activate these neurons. The different hidden layers are set to obtain the least possible error at the output layer. The training applied in Back Propagation is supervised training that means the inputs and outputs of the network are presented, and the error between expected and actual output is determined.
Support Vector Machines (SVMs), as originated from statistical learning approach, are capable classifiers that have been strongly enforced to abundant pattern recognition tasks such as classification and regression. It builds up a hyper plane or set of hyper planes in the greater dimension area that can be applied for classification and pattern recognition. The hyper plane, which has a greater range to the adjacent learning data of each class, is elected to attain excellent splitting and lowering the observation error. Normally, it is applied in binary classification; SVM provides better generalization ability with a decrease in computational difficulty, in addition, to eliminating over fitting of data. Anyhow, the learning time of SVM is high when compared to other training methods and excellent parameters are the challenge to solve while there is non-linearly divisible data. SVM is efficient of applying linear, polynomial or Sigmoid, RBF Kernel functions for activation function that causes it very adaptable.

TRAINING AND TESTING:
Feature vectors are discriminated by the classification such as NB, SVM RBF and NN methods. To promote a strong model, we want to access a formerly arranged data where we have all the inputs, along with the main class. This is known as the learning data, and it is applied to make a model. We also demand to check-ups the efficacy of the made model with other well-known data called the test data. To simplify this activity, the whole well-known data can be separated into learning data and test data. Out of 165 brain MR images, 70% were applied for learning, and 30% were applied for testing. Next, the performance measures are calculated among the 3 classifiers.

Performance measures:
Specificity = TN/ (TN +FP) 100%
Accuracy = (TP +TN)/ (TP+TN+FP+FN) 100%
Sensitivity = TP/ (TP +FN) 100%

Where:
TN (True Negative) = correctly discriminated negative cases, TP (True Positives) = correctly discriminated positive cases, FN (False Negative) = incorrectly discriminated positive cases, FP (False Positives) =

incorrectly discriminated negative cases. Sensitivity is the rate of correctly classified positives, which denotes the best performance of the approach in predicting positives. Specificity calculates how the system behaves to predict the negatives. Accuracy proves the full perfectness of the classifier in estimating both positive and negative cases.

RESULT AND CONCLUSIONS:

The three classification algorithms have been constructed according to MRI brain tumor training data and the performance of the algorithms is then compared according to employing the testing data. R tool is one of the efficient data mining tools used here for executing the classification algorithms. It is an open-source programming language developed by Bell laboratory. This tool is very flexible for writing programs as many algorithms are built with packages.

NB, NN and SVM RBF are trained by GLCM features and classify the brain MRI as an affected image or normal. As Naïve Bayes is stated as an unconditional probabilistic statistic classifier, the attribute has been chosen for classifying the tumor data since this attribute attained the highest conditional probability value among other attributes. According to homom in Bayes algorithm, 55% of data is normal and 45% is abnormal; acquired 92.65% accuracy rate.

NN Figure shows the neural networks with input, hidden and output layers. In this work, 9 inputs feature vectors are applied to input layer and 2 labels (normal, abnormal) are assigned as output layer. The activation function is sigmoid transfer function. The min-max normalization normalize the input data into (0 to 1) range. This work has 3 neurons in its 2 hidden layers. The black lines represent the weights, and the blue line is the bias term. The weights are measured by applying the back propagation method "RPROP" resilient back propagation with weight back tacking. Step max is 100000. The weights are computed with RPROP back propagation and the network converges with error 0.000973 at step 486. The classification accuracy for this method is 99%.

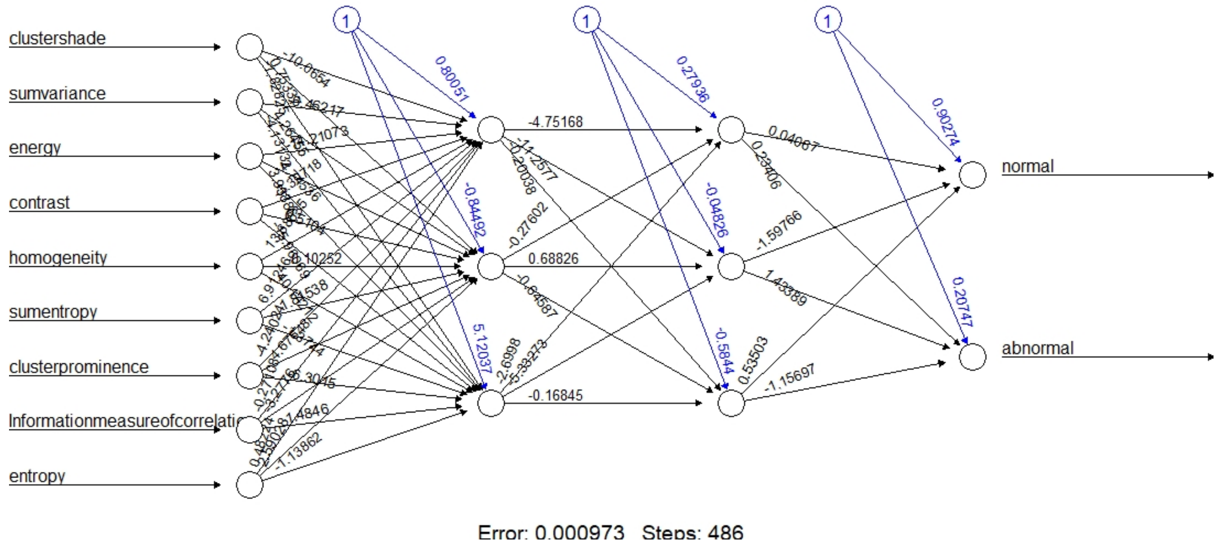

Fig. 4 NN for brain MRI

SVM RBF: In this work, the package (e1071) is used which contains the SVM function. SVM RBF kernel and optimal cost is used in this work. If the cost value is too high, over fit may occur. If the cost value is too small, under fit may occur. Gamma is 0.25 and number of classes is 2. The hyper plane separates the two classes on the accuracy of 97%.

The performance of the classifiers can also express in terms of error measure which is computed by following equation.

$Error\ rate = Number\ of\ misclassification\ instances / Total\ number\ of\ instances$

The error rate in fig. 5 proves that NN algorithm obtained very less misclassification error when comparing it with the other two classification algorithms. The misclassification error in SVM RBF and NB is slightly higher than NN.

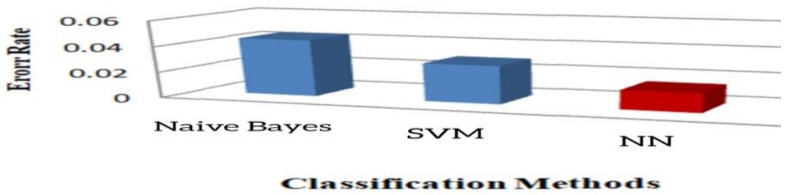

Fig.5 Error rates of different classification methods

Fig. 6 presents classification accuracy, sensitivity, and specificity for 3 methods. It is obviously cleared that NN classification efficiently classified the MRI brain images and predicted with high accuracy when compared with other classification techniques. Table 2 represents the comparative analysis of previous methods with our proposed method.

Conclusion

This work implemented GLCM to extract the features from the brain image dataset. Through the corresponding feature values, the brain data were discriminated and compared by using NB, NN and SVM RBF classification algorithms. It was demonstrated that NN classification powerfully predicted the brain tumor withhold of 99% accuracy.

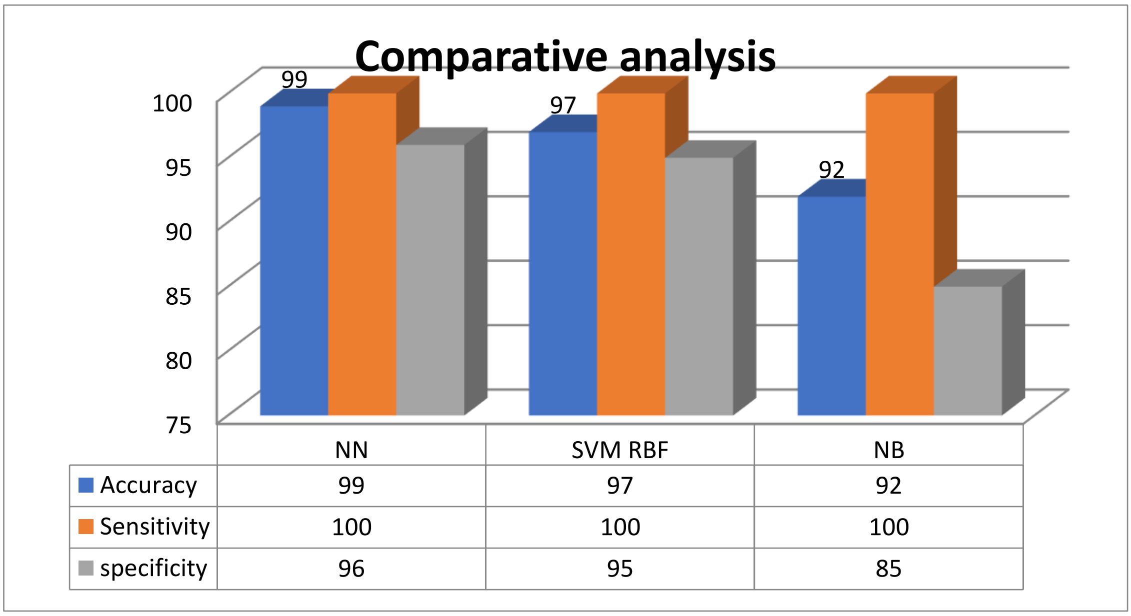

Fig. 6 Comparative analysis of three methods.

Table 2: comparative analysis of previous methods with our proposed method.

Authors	Method	Classifier	Accuracy
Mubashir Ahmad et al[23]	DWT + PCA	SVM LIN	94.7
Nandapuru et al.[24]	GLCM + PCA	SVM	84
Muhammad Nazir et al[25]	Moment features	ANN	94.2
Mohsen H, et al[26]	DWT+PCA	DNN	96.97
Nunzio,et al[27]	DWT + PCA	KNN	98.6
Sudha, et al[28]	GLCM	FFNN and BPN	96.7
Wu et al[29]	DWT + PCA	SVM	96.01
Our proposed method (for Benchmark Brain MR images)	GLCM	NN	99

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