Development of Deep Learning algorithms for Brain Tumor classification using GLCM and Wavelet Packets

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Abstract

Feature extraction and classification are the two major steps involved in computer aided interpretation of tumor.In this paper, technique for classifying three different types of tumor (i.e., meningioma, glioma, and pituitary tumor) namely, hybrid approach (that combines both spatial and spectral properties)is developed. Effectiveness of classification with Recurrent Neural Network is demonstrated for 3 classes of brain tumor. The average classification accuracy of the hybrid approach-based feature extraction is 93.3% in comparison with 88.2% for wavelet packet-based feature extraction and 86.9% for GLCM based approach. Evaluated results show that the proposed method is effective in classification of brain tumor.

Keywords :Wavelet transform, Feature extraction, Multi-resolution analysis, Deep learning, Recurrent Neural network.

1. Introduction

Nowadays, digital images are increasingly used for diagnosisin the medical field. Magnetic Resonance Imaging (MRI) is used as the diagnostic technique for identifying brain tumor. These images are interpreted for decision making [1-3]. Human interpretation is subjective in nature and is dependent on the expertise of the individual. In recent years, computer aided interpretation has become the need of the hour. IT involves the following steps: feature extraction, exemplar generation, training andimplementing the classifier. Considerable researchwork is carried out in this area. Features are extracted both in spatial and spectral domain. These features are then used for exemplar generation and then for training the neural network. However, the precision of classification is strongly dependent on the selection of features and a classification algorithm. In this paper, three different features are determined on the images and Recurrent neural network is used for classification. Section 2 describes the research database.Methodology is explained in Section 3. Results are discussed in Section4.Section 5 provides conclusion and future work.

2. Materials and Methods

Total of 3064 images are obtained from synthetic T1-weighed CE-MRI brain tumor dataset (Meningioma-708, Glioma-1426 and pituitary 930). Size of each image is 512x512.**Figure 1** shows sample of MR images of three classes.

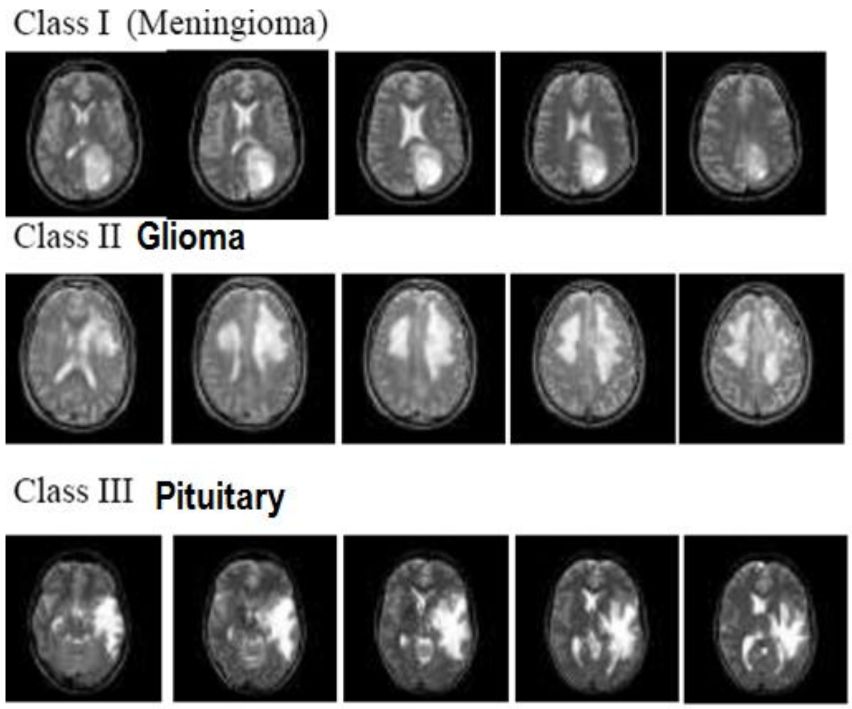

Figure 1 Sample **of MR images of three classes**

3. Methodology of the proposed work

The block diagram of the proposed work is shown in Figure 2. RGB images are converted into gray scale. Features (GLCM, energy and hybrid features) are extracted from the gray scale images. Spectral information is captured with energy of the approximation co-efficient (Each of the four levels of decomposition) [4-8].Texture information is extracted from GLCM features (correlation, energy, homogeneity, entropy) [9-12]. In the third case, GLCM features are obtained on the decomposed co-efficient. With these features, exemplars are created. 75% of the exemplars are used for training and 25% are used for testing. Recurrent Neural Networks are trained with these exemplars and are then used for testing/ implementation. These networks, by virtue has an internal memory and hence is best suited for classification [13-14].Tables 1, 2 and 3 show the exemplar tables with GLCM, wavelet energy and hybrid features. Three different tumors (glioma, Meningioma and pituitary) are coded as 1 2 and 3. These features are normalized whenever necessary for training and testing RNN.

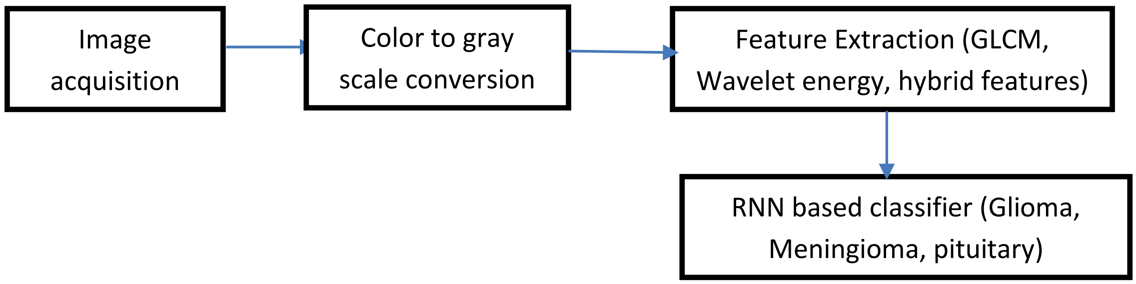

Figure 2 Classification of brain tumor from MRI images

In these exemplar tables, the last column denotes the type of tumor. For facilitating, training and testing of neural network, pituitary is coded as 1, meningioma as 2 and glioma as 3. In Table 1, the number of input parameters is 4.

Table 1 Exemplars with GLCM features

Correlation	Energy	Homogeneity	Entropy	class
0.183082	0.939729	0.954624	0.256073	1
0.182944	0.933868	0.954692	0.247615	1
0.189793	0.939051	0.951574	0.238665	1
0.191613	0.938767	0.950791	0.240442	1
0.189801	0.936589	0.951875	0.24231	1
0.13029	0.969047	0.981116	0.600915	2
0.115834	0.971322	0.988135	0.690854	2
0.186774	0.947085	0.95476	0.357637	2
0.176951	0.94252	0.958805	0.341754	2
0.181094	0.945146	0.95762	0.340961	2
0.158933	0.94865	0.967865	0.355674	3
0.161142	0.945722	0.966658	0.34226	3
0.163696	0.945091	0.966304	0.334739	3
0.152841	0.964167	0.969698	0.342622	3
0.161739	0.967813	0.965295	0.284472	3

Table 2 Exemplars with wavelet energy

Energy at 1st level	Energy at 2ndt level	Energy at 3rd level	Energy at 4th level	class
1.31E+09	1.56E+09	2.1E+09	5.15E+09	1
1.43E+09	1.68E+09	2.22E+09	5.14E+09	1
1.37E+09	1.61E+09	2.15E+09	5.1E+09	1
1.21E+09	1.46E+09	1.99E+09	5.12E+09	1
1.23E+09	1.48E+09	2.01E+09	5.09E+09	1
1.08E+09	1.32E+09	1.88E+09	5.65E+09	2

1.08E+09	1.22E+09	1.78E+09	5.65E+09	2
1.08E+09	1.27E+09	1.84E+09	5.65E+09	2
1.08E+09	1.09E+09	1.64E+09	5.65E+09	2
1.08E+09	1.14E+09	1.69E+09	5.65E+09	2
1.08E+09	1.17E+09	1.72E+09	5.64E+09	3
1.08E+09	1.22E+09	1.78E+09	5.64E+09	3
1.08E+09	1.21E+09	1.77E+09	5.64E+09	3
1.08E+09	1.25E+09	1.81E+09	5.65E+09	3
1.08E+09	1.24E+09	1.8E+09	5.65E+09	3

Table 2 shows the energy of the approximation co-efficient at each of the four levels of decomposition. At each level of decomposition, energy is found to be maximum at the approximation level. In order to improve the performance further, GLCM features are calculated on the approximation and detailed co-efficient (Table 3). In this case, the number of input parameters is 8.

Table3 Exemplars with GLCM features on wavelet co-efficienth level,

Approximation co-efficient				Detailed co-efficient				
Correlation	Energy	Homogeneity	Entropy	Correlation	Energy	Homogeneity	Entropy	class
15.9523	0.27691	0.67981	0.26477	22.75794	0.022791	0.552419	0.208967	1
15.3619	0.30814	0.69039	0.26704	21.0881	0.088146	0.58327	0.216604	1
14.8634	0.32778	0.70866	0.29116	21.13889	0.093506	0.58892	0.222288	1
17.7634	0.19920	0.65559	0.267484	20.7881	0.1109	0.585768	0.20883	1
17.6015	0.22447	0.65843	0.261242	22.8754	0.027191	0.555449	0.213357	1
15.7984	0.29156	0.68445	0.266733	20.9754	0.092369	0.588228	0.219419	2
14.9190	0.32646	0.69592	0.266682	20.34365	0.124727	0.595934	0.216028	2
15.8539	0.28230	0.68839	0.277942	21.22143	0.093707	0.587791	0.220729	2
16.6809	0.25421	0.66968	0.260825	22.29762	0.039691	0.561352	0.209586	2
15.9444	0.26549	0.68180	0.273855	21.08333	0.090766	0.588594	0.221887	2
22.2	0.06914	0.57680	0.225348	24.1746	0.002407	0.557192	0.239902	3
21.2182	0.11276	0.59860	0.22932	24.5714	-0.01305	0.54980	0.23870	3
22.3817	0.06550	0.57260	0.22303	24.1714	-0.00203	0.55462	0.23743	3
21.5611	0.09313	0.58521	0.22262	24.2968	-0.00228	0.55733	0.24237	3
21.9468	0.08461	0.58452	0.22598	23.6174	0.02075	0.56520	0.238702	3

4. Results and Discussion

Evaluation metrics are Sensitivity, Specificity, Classification Accuracy and F-Score .Forevaluating theeffectiveness of the proposed methodology,a confusion matrix is presented in Tables 4-6. These metrics provide information about the accuracy of classification.

Table 4: Confusion Matrix for GLCM Features based Extraction

	Meningioma	Glioma	Pituitary Tumor	Sensitivity	Accuracy	F-Score
Meningioma	150/24 174	0/25 25	0/1 1	100% /48% 87%	86.6%	81.3%
Glioma	0/29 29	150/18 168	0/3 3	100% /36% 84%	88.3%	61.7%
Pituitary Tumor	0/25 25	0/8 8	150/17 167	100% /34% 83.5%	86%	62.1%
Specificity	100%/31.5% 86.5%	100%/ 67% 90.5%	100% /96% 86.5%	**Avg Sensitivity 84.8% Avg. Specificity 87.8%**	**Avg. Accuracy 86.9%**	**Avg. F Score 68%**

Table 5: Confusion Matrix forWavelet packets based Feature Extraction

	Meningioma	Glioma	Pituitary Tumor	Sensitivity	Accuracy	F-Score
Meningioma	144/31 175	2/8 10	4/11 15	96% /62% 87.5%	90.3%	85.7%
Glioma	2/10 12	139/17 156	9/23 32	92.6% /34% 78%	88.3%	59.1%
Pituitary Tumor	6/15 21	5/11 16	139/24 163	92.6% /48% 81.5%	86%	58.4%
Specificity	97.3%/ 75% 91.8%	97.6% /81% 93.5%	95.6% /66% 88.3%	**Avg Sensitivity 82.3% Avg. Specificity 91.2%**	**Avg. Accuracy 88.2%**	**Avg. F Score 67%**

Table 6: Confusion Matrix for Combined Wavelet Packet and GLCM Feature based Extraction

	Meningioma	Glioma	Pituitary Tumor	Sensitivity	Accuracy	F-Score
Meningioma	147/46 193	3/4 7	0/0 0	98% /92% 96.5%	95%	92.8%
Glioma	23/0 23	126/31 157	1/19 20	84% /62% 79%	90%	60%
Pituitary Tumor	0/0 0	0/10 10	150/40 190	100% /80% 95%	95%	63.3%
Specificity	92.3%/100% 94.3%	99% /87% 95,8%	99.6% /81% 95%	**Avg Sensitivity 91% Avg. Specificity 95%**	**Avg. Accuracy 93.3%**	**Avg. F Score 72%**

From Tables 4and 5, it is clear that features from wavelet packets provide better classification accuracy results than GLCM features. GLCM based texture features characterize pairwise relation between two neighboring pixels. It describes the texture of the image. Coarse and fine intensity variations are captured by these features. Coarse intensity variation can be best captured in spatial domain. Wavelet decomposition separates both the coarse intensity variation (approximation co-efficient) and fine (abrupt) intensity variation (detailed co-efficient). Having separated the co-efficient, energy of these approximation and detailed co-efficientare the indicators of abnormality. Hence features from wavelet packets outperform that of the GLCM features. However,texture features on the detailed and approximation co-efficient can capture the coarse and fine intensity variations better than energy.

5. Conclusion

Brain tumor classification plays a very important role in diagnostic procedures. Accurate classification through machine learning not only makes clinical diagnosis easy but also increases the chance of subject's survival tremendously. In this paper, a hybrid approach that combines GLCM and wavelet packets for feature extraction has been proposed. RNN which is associated with the vanishing gradientproblem classifies benign andmalignant tumor. It is based on sequences of ultrasoundimages and is proved that the predictive accuracyof this sequential classification is higher than making decisionbased on independent single images.Temporal fusion of these images will result in accurate diagnosis and classification of tumor.

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