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RESEARCH ARTICLE

MOR-GDCNN: MOTOR NERVOUS DISEASE IDENTIFICATION VIA GATED DILATED CONVOLUTIONAL NEURAL NETWORK WITH DTI IMAGES

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Abstract –A neurodegenerative disorder termed motor neuron disease (MND) affects the cerebral cortex, the cerebellum, and spine cord's top and bottom motor neurons. MND is a rare nervous system disorder, is frequently subject to misdiagnosis due to its potential to resemble various disorders, notably cervical myelopathy, at its initial stages. The early detection of MND poses a challenge. Reports indicate diagnostic delays ranging from eight to over fifteen months, with a median time of 12 months from onset to diagnosis in patients with spinal onset. Early MND detection is difficult, and manual identification takes a lot of time. To overcome these challenges, Model is proposed for the identification of MND cases. In this research paper, a novel deep learning (DL) based MOR-GDCNN has been suggested for MND case identification. The Gaussian adaptive bilateral (GAB) filter is used to pre-process the images that are provided to progress the quality of image. The gated dilated convolutional neural network (GD-CNN) is then utilized to extract the features from the images. Finally, the images are classified into normal and abnormal cases utilizing support vector machine (SVM) approach.

Keywords – *motor neuron disease, Support vector machine, Gated Dilated Convolutional Neural Network, Gaussian adaptive bilateral.*

1. INTRODUCTION

The devastating neurodegenerative illnesses identified as MND impact the nerve cells that regulate voluntary motions of the body. The MND illnesses are defined by the slow degradation of motor cells [1-2]. Raising the standard of living for persons with MND necessitates early diagnosis and effective care, yet due to the scope and complexity of these conditions, these activities usually present significant hurdles. Pain is a usual sign of MND, but when it appears before weakness occurs, it is often misdiagnosed as something else. The disease is persistent and progressive. Patients are often assigned to non-neurological agencies due to atypical symptoms, which may result in a delayed diagnosis and inappropriate treatment [3].

In recent years, DL [4] has arisen in the fields of medical imaging analysis and illness categorization. These models, which use a range of data sources like as EMG signals, MRI [5] scans, and patient clinical histories, can aid in the early diagnosis and exact classification of MND.As a rare nerve system ailment, MND has frequently been misdiagnosed since it can first present with symptoms of other illnesses, including cervical myelopathy. Since MND nearly often manifests as a gradual onset, early diagnosis might be challenging. According to reports, the diagnostic delay in MND can last anywhere from eight to over fifteen months. Thus, having a deeper comprehension of the symptoms of MND can aid in an early diagnosis and have important ramifications for getting access to the right treatment and care.

One of the key advantages of employing DL for the classification of motor nervous diseases lies in its capacity to glean insights from extensive datasets. DL models increase their diagnostic accuracy by extrapolating their expertise by training on comprehensive and varied datasets that include data from patients at different disease stages and demographics [6]. The early stage of MND poses challenges for diagnosis, making it a formidable task. Artificial intelligence (AI) [7] has grown significantly in recent years in a wide range of scientific disciplines [8-9]. However, manual identification takes a long time, and early detection of MND remains a challenging endeavor. To address this, a novel DL model is proposed that distinguishes between normal and abnormal MND occurrences. The following is the main contribution of the suggested DL model.

- Initially, the GAB filter is used to pre-process the images that are provided to improve the quality of image.
- Then, the GD-CNN is then utilized to extract the features from the images.
- Finally, the images are classified into normal and abnormal cases utilizing SVM approach.

The remaining phase of the research are as follows. Section 2 provides a summary of the relevant works, Section 3 offers the suggested MOR-GDCNN Model for motor nervous disease detection, and Section 4 presents the outcomes. Section 5 concludes the paper and discusses further research.

2.LITERATURE SURVEY

Many investigators take previously published papers identifying both normal and atypical cases of MND using digital image processing and classification approaches. A wide range of material has been produced regarding the latest advancements in ML and DL methods.

In 2019 Lauraitis, A., et al. [10] proposed an approach for task-based assessment of nerve system MND. The data is analyzed by a back-propagation neural network (BPNN) classifier, which produces results. 86.4% of the time, early prodromal symptoms of CNS motor diseases can be successfully identified. Compared to previous models, the suggested approach exhibits a low dependability rate.

In 2020, Zhang, K. et al. [11] developed a mixed neural network to identify data from mental images. A generative adversarial network-based DA technique has been proposed to improve the classification of MI functions. The level of accuracy attained is still insufficient.

In 2021 Greco, A et al., [12] recommend identifying and categorizing Motor involvement of both the upper and lower limbs in some patients' nerves using simply blood data. The experiment's categorization accuracy rate was 94%, and the results indicate a lower rate than previous methods.

In 2022 Bede, P et al., [13] provided a phenotypic classification of each patient's MND based on changes in radiological disease load. Amyotrophic lateral sclerosis was categorized with 93.7% accuracy using the MLP rate of classification, whereas primary lateral sclerosis was identified with a 43.8% accuracy rate.

In 2023 Toh, C et al., [14] recommend MRI scans of the brain and spine in the same area to detect direct neurodegeneration in motor neuron disease. MRIs were available for a group of 75 MND patients and 13 healthy controls. Although 95% of the experiment is successful, the reliability level is insufficient for detection.

A variety of methods have recently been used to detect MND, as described in the studies above. Researchers used approaches such as preliminary image processing to determine and categorize diseases, segmenting the ripening portions, and categorizing diseases using some training models.

3.PROPOSED METHOD

In this paper, a novel DL based MOR-GDCNN model has been suggested for MND case identification. The GAB filter is used to pre-process the images that are provided to improve the quality of image. The GD-CNN is then utilized to extract the features from the images. Finally, the images are classified into normal and abnormal cases utilizing SVM approach. Figure 1 shows the proposed MOR-GDCNN methodology.

3.1 Data Pre-Processing

During the pre-processing step, the GAB filter is used to reduce distortion in the input pictures. The GAB filter effectively denoises medical pictures by combining bilateral filtering and adaptive parameter adjustments. The suggested technique greatly improves image quality. Equation (1) illustrates how the bilateral filter, input picture $i_{\mathcal{P}}$ and guiding $\mathcal{A}_{\mathcal{g}}$ differ:

$$\hbar(n) = \sum_m \left(W^{\mathcal{A}_{\mathcal{g}}}_{n,m}\right)(\mathcal{A}_{\mathcal{g}}) i_m \quad (1)$$

$$W^{G_d}_{v,u} = \frac{1}{Nor_f} \exp\left[-\left\|\frac{n-m}{-\sigma_c^2}\right\|^2\right] \quad (2)$$

$\mathbb{N}_i$ is the normalization factor, as indicated by equation (2) above. The GAB kernel is defined in equation (2), where the Gaussian spatial filter is represented by $\exp\left[-\left\|\frac{n-m}{-\sigma_c^2}\right\|^2\right]$ in equation (3).

$$\mathcal{Q}^{G_d}_{v,u}(i, \mathcal{g}^-) = \frac{1}{\mathbb{N}_i} \exp\left[-\left\|\frac{n-m}{-\sigma_c^2}\right\|^2\right] exp\left[-\left\|\frac{I_n - \mathcal{A}_{\mathcal{g}}{}^-}{-\sigma_e^2}\right\|^2\right] \quad (3)$$

Where, $-\sigma_c^2$ characterise the difference in intensities. $\mathcal{A}_{\mathcal{g}}{}^-$ obtained from equations (1) and (3) and $\exp\left[-\left\|\frac{n-m}{-\sigma_c^2}\right\|^2\right]$ is the range kernel.

3.2 Feature Extraction of MND

In this phase the enhanced features are extracted using DL-based GD-CNN approach. The following features were utilizing in GD-CNN framework for MND classification. By using dilated convolutions rather than regular convolutions, this architecture allows for a wider receptivity area without seeing a spike in parameters. A variant of the conventional convolution process is the dilated convolution approach. In particular, equation (4) expresses the convolution process with attributes of the input $\mathfrak{i}_{\mathfrak{p}ut}$ and a filter $\mathfrak{f}_{\partial}$.

$$\left(\mathfrak{i}_{\mathfrak{p}} \times \mathfrak{f}_{\partial}\right)(\mathfrak{g}, \mathfrak{t}) = \sum_{\mathfrak{c}} \sum_{\mathfrak{d}} \mathfrak{i}_{\mathfrak{p}}\left(\mathfrak{g} - \mathfrak{c} * \mathfrak{r}_{\mathfrak{v}}, \mathcal{F} - \mathfrak{d} * \mathfrak{r}_{\mathfrak{v}}\right)\mathfrak{f}_{\partial}(\mathfrak{u}, \mathfrak{v}) \quad (4)$$

The dilated rate is represented by $\mathfrak{r}_{\mathfrak{v}}$ in the equation. The image integrating matrix $\mathcal{Y}_a$ is continually scanned by the convolution kernel. Dilated convolutions increase the scanning feature interval by adding a few spaces between convolution kernels. The feature $\mathfrak{f}_{\mathfrak{a}}$ is extracted after the convolution procedure and is represented in equation (6).

$$\mathfrak{f}_{\mathfrak{a}} = \mathfrak{i}_{\mathfrak{p}ut}(\mathfrak{w}' \times \mathcal{Z}^{\mathfrak{g}}_{\mathfrak{o}:\mathfrak{o}+\mathfrak{a}-1} + \mathfrak{d}) \quad (5)$$

$$\mathfrak{Z}_{\mathfrak{h}} = \mathbb{K}_{\mathfrak{a}} = \mathfrak{v}\mathfrak{a}\mathrm{I}_{\mathfrak{a}} = \mathcal{O}_{\mathfrak{p}\mathfrak{u}\mathfrak{t}} \quad (6)$$

The results of the convolution are shown as $\mathcal{O}ut_{\mathfrak{p}}$, the initial values for the input matrix $\mathfrak{Z}_{\mathfrak{h}}$, vital matrix $\mathbb{K}_{\mathfrak{a}}$, and rate matrix $\mathscr{v}\mathfrak{a}\mathfrak{l}_{\mathfrak{a}}$ respectively, based on the evaluation above. The best selective deep characteristics of MND are used to categorize the test images.

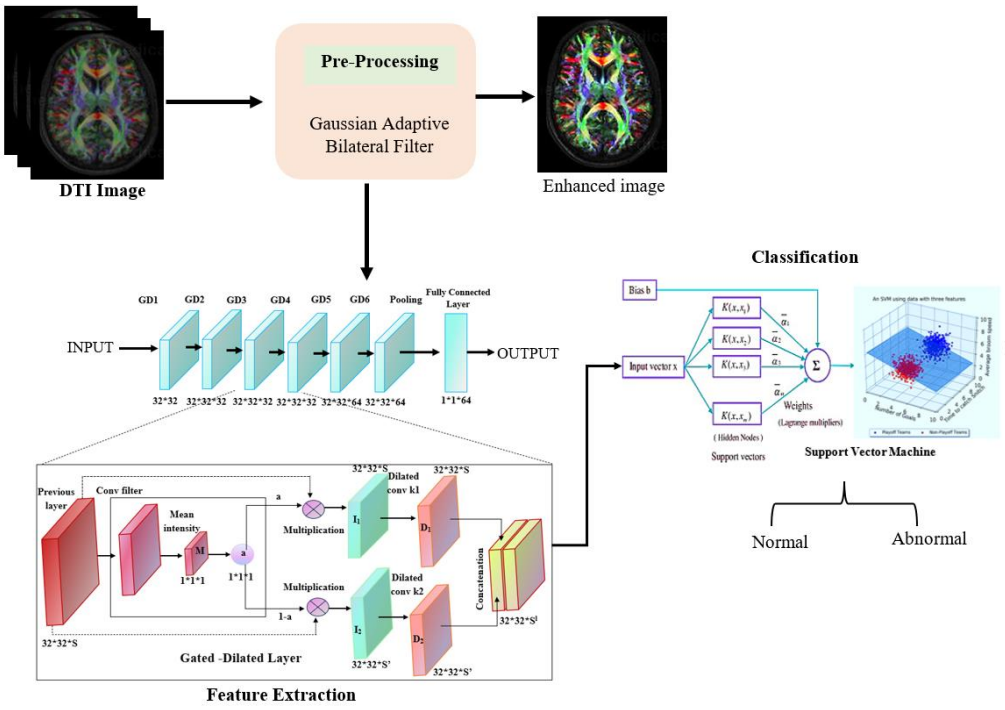

Figure1. Proposed MOR-GDCNN model

3.3 Classification

In this section, the extracted images are utilized for identifying the cases of MND using SVM model. Figure 2 shows the architecture of GD-SVM.

SVM are valuable for predicting ozone depletion in classification. As supervised algorithms, they perform well in both categorization and regression problems. SVMs, in contrast to neural networks, use a single layer for displaying feature vectors in the input space during the decision-making process. The kernel function efficiently captures analogies between data points, with examples like polynomial, RBF, and linear kernels.SVMs determine the optimal border for non-linearly separable examples using the kernel method and a flexible margin. Finally, the images are classified into normal and abnormal cases of MND.

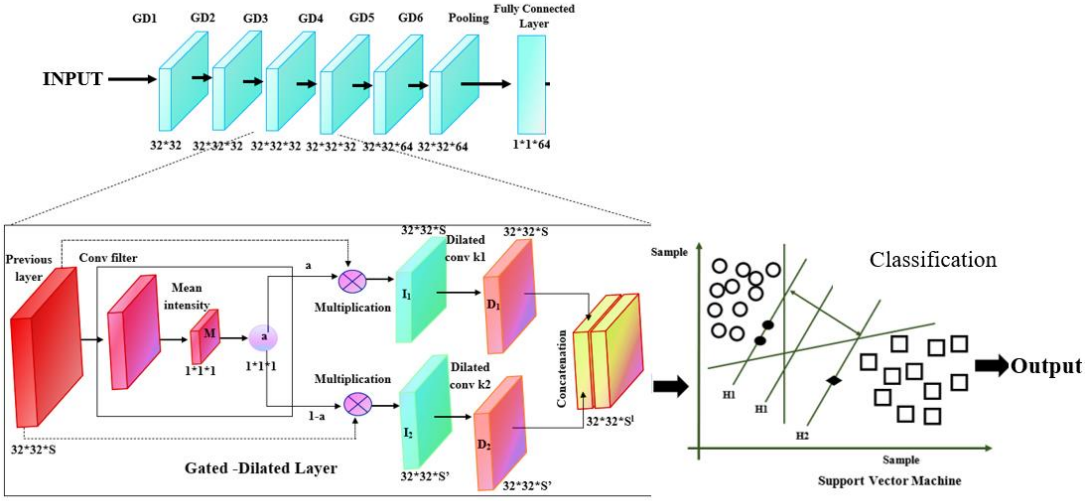

Figure2. Architecture of GD-SVM model

4. RESULT AND DISCUSSION

The collected dataset is utilized to classify MND. Figure 3 shows the experimental results of the recommended MOR-GDCNN model based on the obtained dataset. In order to reduce noise and enhance the input images. the GAB filter (column 2) is applied as a pre-processing step (column 1). At the same time, these previously processed photos are provided (column 3) for GD-CNN feature extraction. Finally, the SVM categorizes MND instances into normal and pathological categories (column 4).

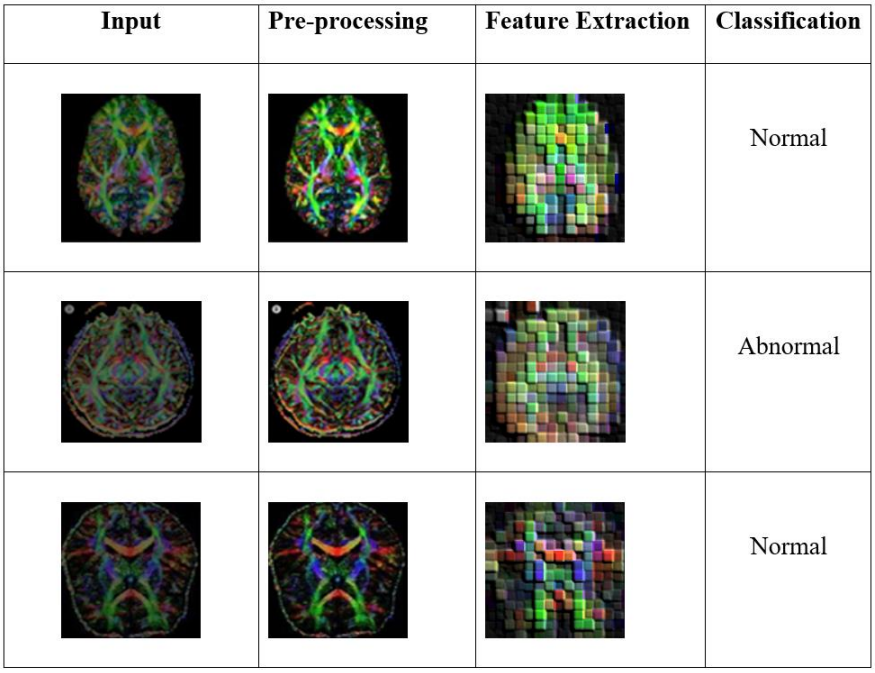

Figure3. Experimental outcomes of the proposed Model

4.1 Performance Analysis

The investigations' findings illustrate the distinctive features of the MND recognition. Basic variables like True Positive ($T_R P_v{}^+$), True Negative ($T_R N_v{}^+$), False Positive ($f_A P_v{}^+$) and False Negative ($f_A N_v{}^+$) is employed to supply the rating metrics that are analysed.

$$A = \frac{T_R P_v{}^+ + T_R N_v{}^+}{T_R P_v{}^+ + T_R N_v{}^+ + f_A P_v{}^+ + f_A N_v{}^+} \times 100 \quad (7)$$

$$P = \frac{T_R P_v{}^+}{T_R P_v{}^+ + f_l P_v{}^+} \quad (8)$$

$$Re = \frac{T_R P_v{}^+}{T_R P_v{}^+ + f_A P_v{}^+} \quad (9)$$

$$F1 - Score = \frac{2PrRe}{Pr+Re} \quad (10)$$

Table 1. Evaluation outcomes of the proposed model

Classes	Accuracy	Precision	Recall	Specificity	F1 score
Normal	99.74	98.19	98.43	97.65	98.77
Abnormal	99.78	97.34	97.59	96.76	98.22

The table 1 demonstrates the suggested model classified early stages of MND, including normal and atypical patients. The success percentage of the suggested model is 99.75%.

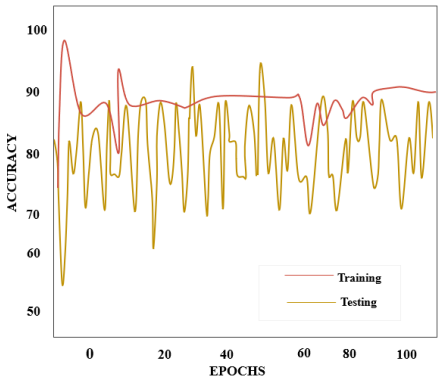

Figure4. Accuracy curve of the proposed model

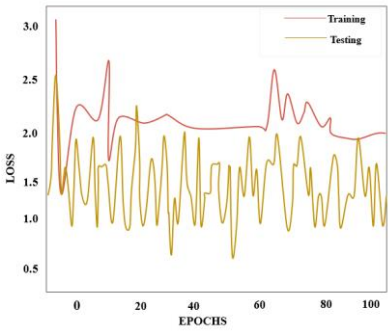

Figure 5. Loss curve of the proposed model

The proposed Duple model classifies the early phases of MND using collected DTI images. The suggested model obtained 99.75% testing accuracy with a low proportion of errors, depending on the 100 number of epochs.

4.2 Comparative analysis

The accuracy of each neural network was assessed to demonstrate that the model outputs seemed more reliable. The performance of four neural network classifiers in the recommended model was evaluated: gated dilated, CNN, and Dilated CNN.

Table 2 displays the maximal categorization capacity across many common DL connections. However, the proposed MOR-GDCNN model resulted in more severe fallout than typical DL networks. The recommended GD-CNN increases the total f1-score by 2.67%, 3.64%, and 4.47%, respectively.

Table2. Comparison with traditional models

Networks	Accuracy	Precision	Recall	Specificity	F1 score
Gated dilated	97.25	97.27	96.36	95.44	97.07
CNN	96.17	95.78	97.45	97.35	96.25
Dilated CNN	95.18	94.34	95.63	95.11	95.42
Proposed GD-CNN	98.89	98.29	97.31	97.72	98.84

Table3. Contrasted the suggested model with existing approaches.

Techniques	Accuracy	Precision	Recall	Specificity	F1 score
Res Net	98.47	97.67	96.46	95.39	97.37
Alex Net	98.27	95.89	96.33	97.56	96.45
Proposed SVM	99.13	97.29	98.23	96.77	98.75

However, the table 3 SVM model produced more robust results than the conventional DL networks. Applying the SVM model, the total f1-Score increases by 3.6%, 3.69%, and 2.7%, respectively.

Table 4. Accuracy contrast between existing methods and proposed Duple MONDNet

AUTHOR	METHODS	ACCURACY
Lauraitis, A et al., [10]	BPNN	86.4%
Greco, A et al., [12]	SVM-RFE	94%
Bede, P et al., [13]	MLP	93.7%
Proposed model	GD-SVM	99.66%

The outcomes of the trial for the photos from the obtained dataset are displayed in Table 4. The efficacy of classification was employed as a performance criterion while evaluating previous models. When the Model is compared against BPNN, SVM-RFE, and MLP, the f1-score ranges are usually 13.26%, 5.56%, and 5.96%, respectively.

5. CONCLUSION

In this paper, a novel DL based MOR-GDCNN model is suggested for MND case identification. The GAB filter is used to pre-process the images that are provided to improve the quality of image. The GD-CNN is then utilized to extract the features from the images. Finally, the images are classified into normal and abnormal cases utilizing SVM approach. According to the test outcomeshe suggested model has yield 99.75% accuracy rate for the categorization of MND cases. The suggested GD-CNN increases the f1-Score by 2.67%, 3.64%, and 4.47%.The overall f1-Score is improved by 3.6%, 3.69%, and 2.7% with the SVM model. Comparing the suggested typical to BPNN, SVM-RFE, and MLP characteristically outcomes in the f1-score 13.26%, 5.56%, and 5.96% respectively. In future, the suggested model is extended with advance DL methods for improving the diagnosis rate

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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