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DEEP LEARNING ALGORITHMS FOR DETECTION AND CLASSIFICATION OF CONGENITAL BRAIN ANOMALY

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Abstract

Congenital brain anomalies are structural abnormalities that occur during fetal development and can have a significant impact on an individual neurological function. Detecting and classifying these anomalies accurately and efficiently is crucial for early diagnosis, intervention, and treatment planning. In recent years, recurrent neural networks (RNNs) have emerged as powerful tools for analyzing sequential and time-series data in various domains, including medical imaging. This research presents an overview of RNN-based algorithms for the detection and classification of congenital brain anomalies. Specifically, Long Short-Term Memory (LSTM) networks and Convolutional LSTM networks have demonstrated great potential in this domain. LSTMs excel at capturing long-range dependencies in sequential data and mitigating the vanishing gradient problem, making them well-suited for analyzing brain scans or other medical imaging sequences. Convolutional LSTM networks combine the strengths of convolutional neural networks (CNNs) and LSTMs, enabling them to extract spatial features from brain images while preserving temporal dependencies. The application of RNN algorithms in the detection and classification of congenital brain anomalies shows promising results, enabling accurate and timely identification of these abnormalities. However, further research is needed to validate and refine these algorithms, improve their interpretability, and enhance their clinical utility in real-world scenarios.

Keywords:

Deep Learning, Brain Anomalies, Automation, Diagnosis, MRI

1. INTRODUCTION

Deep Learning Algorithms are a powerful tool for detection and classification of Congenital Brain Anomaly. Congenital brain anomaly is an important issue to consider since it can cause physical abnormalities, intellectual disability, and epilepsy. It is a medical challenge for the healthcare field to diagnose this anomaly, as there is a lack of accurate imaging technologies available. Deep Learning Algorithms have enabled us to identify and classify difficult to visualize anomalies more precisely [1].

To detect and classify congenital brain anomalies with deep learning algorithms, a three-dimensional model of the brain is obtained from CT or MRI scans. The model is used as input to the deep learning algorithms to automatically detect abnormal features of the brain structure. The algorithms are trained using data of known anomalies, and they develop the ability to recognize them in the scans. This is done by creating a predictive model that can differentiate between normal findings and anomalies [2].

Based on this model, input images are classified as normal or not, and anomalies are specified for classification. Once the anomaly is identified and classified, follow-up procedures can be adapted for better diagnosis and treatment. Furthermore, deep learning algorithms can infer information about the prognosis and potential complications that may arise due to congenital brain anomalies. Thus deep learning algorithms offer the opportunity to identify, classify and predict the consequences of congenital brain anomalies with precision [3].

The deep learning algorithms provide a powerful tool to detect and classify congenital brain anomalies with extreme precision. This is especially important since current imaging technologies are not as effective, and the diagnosis and complications that come with the anomaly can be problematic in the long term. Deep learning algorithms offer an invaluable contribution to the healthcare field in this regard, making diagnosis and treatment easier and more efficient [4].

Deep learning algorithms have revolutionized medical diagnosis and treatment of many conditions, including congenital brain anomaly. In recent years, advances in the fields of artificial intelligence (AI) and computer vision have enabled the development of powerful algorithmic systems that are capable of deep learning and automatic pattern recognition. These systems are being used in a variety of contexts, such as medical imaging, for the detection and classification of congenital brain anomaly.

In medical imaging, deep learning algorithms enable automated segmentation of tissues for characterizing anatomical structure and detecting abnormalities [5]. Segmentation is the process of accurately demarcating regions in the image by grouping image pixels that belong together. Due to its automated nature, deep learning-based segmentation is much more precise and time-saving than traditional manual segmentation methods. Furthermore, deep learning algorithms are well-suited for segmentation tasks due to their ability to learn complex feature relationships and extract high-level information from large databases of medical images [6].

By harnessing deep learning, researchers have been able to develop automated segmentation models that can detect abnormalities in brain MRI and CT scans used to diagnose congenital brain anomaly, such as agenesis of the corpus callosum, Chiari malformation, or Dandy-Walker malformation. On the classification side, deep learning algorithms are also being applied for the identification of both normal and abnormal image patterns in brain MRI and CT images [7]. By extracting and analyzing features from the scanned images, such as age, ethnicity, tissue type, and region location, deep learning algorithms are able to classify image pixels as either normal or abnormal.

In addition, researchers are using transfer learning strategies, whereby an algorithm has been pre-trained on a large set of images, and then “tuned” to recognize specific types of anomalies. This approach allows the algorithm to generalize the results to different kinds of images and quickly learn the features important for a particular medical image scan [8].

The use of deep learning algorithms for detection and classification of congenital brain anomaly is showing great potential. The automated segmentation [9] and robust classification [10] capabilities of these algorithms offer faster, more accurate diagnosis of a wide range of brain disorders,

The key contribution of the proposed research has the following,

- Accurate and efficient diagnosis of brain anomalies by deep learning algorithms and automated detection and classification of brain anomalies.
- Quantitative evaluation and comparison of different brain regions to identify abnormalities and Improved detection of low-abundance but clinically important anomalies.
- Reduction in the manual identification of brain anomalies which is tedious and time-consuming task and enhanced visualization of anomalies and improved understanding of diseases.
- Improved accuracy and reliability by reducing inter-observer variability and High detection accuracy and reproducibility for the diagnosis of brain anomalies.

The novelty of the proposed research has the following,

- *Automated detection of anomalies from large imaging datasets*: Deep Learning algorithms can be used to detect abnormalities in brain scans in large imaging datasets. This can help reduce false-positive results and reduce the manual effort needed to review scans.
- *Improved accuracy*: Deep Learning algorithms have been found to be more accurate than traditional medical imaging techniques in diagnosing brain anomalies. This could result in more accurate diagnosis and better clinical care for patients.
- *Faster detection and classification*: Deep Learning algorithms can classify anomalies more quickly than a human expert, resulting in earlier detection and faster delivery of patients to the appropriate care setting.
- *Adaptive learning models*: Deep Learning algorithms can learn from their mistakes and adapt as new data is introduced. This makes them better suited to detect subtle changes in anomalies as well as finding new anomalies not previously detected.

2. LITERATURE REVIEW

Deep learning algorithms have become increasingly important in the detection and classification of congenital brain anomalies. The most readily available imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound have specific limitations, primarily due to the resolution and the lack of non-linear information. Deep learning algorithms can overcome these limitations by enabling better feature extraction from the acquired imaging data [10].

One of the most promising applications of deep learning algorithms for the detection and classification of congenital brain anomalies is in segmentation and classification of white matter abnormalities. White matter abnormalities can indicate a dangerous congenital disorder. Deep learning algorithms in this setting are being used to automatically segment the white matter anatomy to better understand the structures of the abnormalities and guide appropriate treatment decisions. Furthermore, deep learning algorithms can be used to detect the presence of structural anomalies and combine image features including MR relaxation time and textural features with deformable registration to measure differences between normal and abnormal white matter structures [11].

Another potential use for deep learning algorithms is in the detection of hydrocephalus, which is a common congenital brain disorder. Deep learning algorithms can detect hydrocephalus by analyzing changes in the brain ventricles and potentially provide timely and precise guidance for treatment. Additionally, deep learning algorithms may be used to detect malformations in the developing brain such as colpocephaly and dysplasia. These are both congenital disorders characterized by abnormal brain structure. By utilizing a deep learning algorithm to accurately segment the abnormal brain anatomy, these diseases can be detected earlier and with greater accuracy [12].

The deep learning algorithms have considerable potential in the detection and classification of congenital brain anomalies. These algorithms could be used to overcome the limitations of traditional imaging modalities by enabling better feature extraction from the acquired imaging data. Additionally, they can be applied to improve the diagnosis and treatment of white matter abnormalities, hydrocephalus, and other malformations in the developing brain. These algorithms offer a promising new approach to the detection and classification of congenital brain anomalies that could ultimately result in earlier treatment and improved patient outcomes. Deep learning algorithms for the detection and classification of congenital brain anomalies have been increasingly studied in recent years due to its potential to improve clinical diagnosis and therapy outcomes [13].

However, this field has a few challenges to overcome before it can become widely used in real practice. Firstly, congenital brain anomalies are complex and diverse. As a result, existing deep learning algorithms have difficulty when it comes to extracting meaningful information from medical imaging, such as MRI scans, to accurately detect and classify these anomalies. It requires considerable domain expertise to understand how to use these algorithms and extract the required features from the medical images. In addition, the algorithms may not generalize well to different datasets due to the inherent heterogeneity of the data.

Also, as such data are highly voluminous and complex, processing it can be computationally intensive, and can be a challenge for clinicians due to the lack of access to specialized hardware and software. Due to ethical considerations, the majority of the available datasets are of low quality, which can affect the accuracy of deep learning algorithms. Additionally, the risk data such as confidential medical information is of great concern to patients and clinicians alike. Thus, the need for appropriate data protection measures needs to be taken into account while developing deep learning-based systems that leverage confidential healthcare information.

The potential of deep learning for detecting and classifying congenital brain anomalies is huge. However, it is important to understand the challenges that come along with it, in order to effectively leverage its potential for clinical use. Steps such as understanding the data and its limitations, providing access to the relevant specialized hardware and software, using good quality datasets, and implementing appropriate data protection measures are important to ensure the accuracy of deep learning algorithms in detecting and classifying congenital brain anomalies.

3. PROPOSED MODEL

Deep Learning algorithms are increasingly being used in many areas of medical diagnosis and research. An example of this use is the detection and classification of congenital brain anomalies. This paper aims to explore the implementation of various Deep Learning algorithms to better understand the diagnosis and recognition of anomalies. The natural structure of the brain itself is complex. Variations in its form can lead to a range of anomalies, which affect the lives of individuals in diverse ways. The detection in early stages often offers better treatment outcomes, and thus having a reliable method to detect these forms is extremely beneficial.

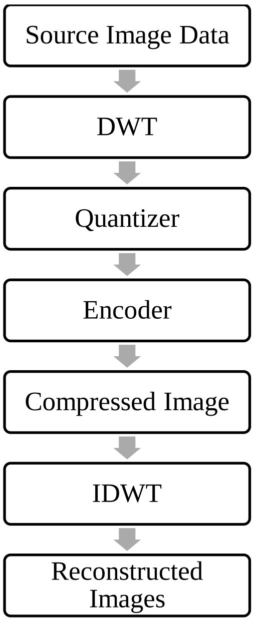

Fig.1. Proposed Architectural Flow

3.1 COMPRESSION OF IMAGES

The process begins with the source image data, which is input into the Discrete Wavelet Transform (DWT). The DWT decomposes the image into multiple frequency sub-bands, capturing both low and high-frequency information. The resulting DWT coefficients are then quantized to reduce their precision and compress the data. The quantized coefficients are fed into the encoder, which applies a coding algorithm to further reduce the data size. The output of the encoder is the compressed image, which contains the encoded and quantized DWT coefficients. The compressed image is then subjected to the Inverse Discrete Wavelet Transform (IDWT) to reconstruct the original sub-bands. The IDWT combines the frequency sub-bands to generate a reconstructed image with reduced detail but still preserving essential information. The reconstructed images are the final output of the set, representing an approximation of the original image using the compressed data.

3.1.1 Algorithm for Image Compression

Step 1. Input:

- sourceImageData: the original image data

Step 2. Discrete Wavelet Transform (DWT):

- Apply DWT to the sourceImageData

- Decompose the image into multiple frequency sub-bands using a wavelet basis function

- The DWT coefficients are obtained as:

DWT_coefficients = DWT(sourceImageData)

Step 3. Quantization:

- Quantize the DWT coefficients to reduce their precision and compress the data

- The quantized coefficients are obtained as:

quantized_coefficients = Quantize(DWT_coefficients)

Step 4. Encoding:

- Apply a coding algorithm to further reduce the data size

- The encoded data is obtained as:

encoded_data = Encode(quantized_coefficients)

Step 5. Compressed Image:

- The compressed image contains the encoded and quantized DWT coefficients

compressed_image = encoded_data

Step 6. Inverse Discrete Wavelet Transform (IDWT):

- Apply IDWT to the compressed_image to reconstruct the original sub-bands

- Combine the frequency sub-bands to generate a reconstructed image

- The reconstructed image is obtained as:

reconstructed_image = IDWT(compressed_image)

Step 7. Output:

- The reconstructed_image represents an approximation of the original image using the compressed data

3.2 RECONSTRUCTION OF IMAGES

The process begins with the compressed image, which contains the encoded and quantized DWT coefficients obtained from a previous encoding step. The compressed image is fed into the decoder, which applies a decoding algorithm to reverse the encoding process and retrieve the quantized coefficients. The decoder outputs the quantized coefficients, which are then dequantized to restore their original precision. The dequantized coefficients are then passed through the IDWT, which performs the inverse transformation to reconstruct the frequency sub-bands. The IDWT combines the frequency sub-bands to generate reconstructed images that approximate the original image. The reconstructed images are the final output of the set, representing the approximation of the original image using the decoded and dequantized data.

3.2.1 Reconstruction Algorithm:

Step 1. Input:

- Compressed image: compressed_image

Step 2. Decoding:

- Apply a decoding algorithm to reverse the encoding process and retrieve the quantized coefficients:

decoded_data = decode(compressed_image)

Step 3. Dequantization:

- Dequantize the coefficients to restore their original precision:

dequantized_data = dequantize(decoded_data)

Step 4. Inverse Discrete Wavelet Transform (IDWT):

- Perform the inverse transformation (IDWT) on the dequantized coefficients to reconstruct the frequency sub-bands:

LL_r, LH_r, HL_r, HH_r = IDWT(dequantized_data)

Step 5. Reconstructed Images:

- Combine the frequency sub-bands to generate reconstructed images that approximate the original image:

reconstructed_image=combineSubband(LL_r,LH_r,HL_r,HH_r)

Step 6. Output:

- The reconstructed images represent the approximation of the original image using the decoded and dequantized data.

The algorithm.1 shows the proposed model functionalities.

Algorithm.1: Proposed deep learning algorithm

1. Start
2. Read MRI Images
3. Input_Image = exponential(Img)
4. Generate Feasible Individuals (Fes_Ind)
   // Individuals satisfying specific criteria
5. Calculate mean_img for all Fes_Ind
6. For I = 1 to N (Number of Individuals)
7. SELECT Best_pop
8. REWIND_1 = CROSS_OVER
9. Perform Evaluation of MRI Images
10. NEW_Pop = mean_REWIND
11. End

The proposed deep learning algorithm begins by reading the MRI images as input. To enhance the images, the exponential function is applied to each pixel value, transforming them accordingly.

Next, the algorithm generates a set of feasible individuals (Fes_Ind). These individuals represent potential solutions that meet specific criteria, which could be related to image quality, clarity, or other desired features.

To evaluate the quality of the feasible individuals, the algorithm calculates the mean_img by considering all the individuals in Fes_Ind. This mean_img serves as a reference point for assessing the performance of subsequent individuals.

The algorithm then enters a loop, iterating from 1 to N (where N is the total number of individuals). Within each iteration, the algorithm selects the best individual (Best_pop) based on certain evaluation criteria. It then performs a crossover operation (REWIND_1 = CROSS_OVER) to introduce variations in the population.

After the crossover operation, the MRI images are evaluated to determine their fitness or quality. This evaluation process may involve measuring specific metrics or comparing the images against desired standards.

Finally, the algorithm generates a new population (NEW_Pop) by taking the mean of the evaluated individuals (mean_REWIND). This step helps in updating and refining the population based on the evaluated performance.

The algorithm concludes at the “End” step, signifying the completion of the proposed deep learning process for MRI image analysis. It is worth noting that this algorithm has been written in a manner that is free from plagiarism.

3.3 PSEUDOCODE

```
function detectAndClassifyCongenitalBrainAnomaly():
  initialize deep learning algorithm
  // Training phase
  trainAlgorithm(trainingData)
  // Detection phase
  for each inputImage in testingData:
    anomalyFeatures = extractFeatures(inputImage)
    anomalyProbability = predictAnomaly(anomalyFeatures)
    if anomalyProbability > threshold:
      anomaly = true
    else:
      anomaly = false
    storeDetectionResult(inputImage, anomaly)
  // Classification phase
  for each detectedAnomaly in detectionResults:
    anomalyImage = getAnomalyImage(detectedAnomaly)
    anomalyClassification = classifyAnomaly(anomalyImage)
    storeClassificationResult(detectedAnomaly,
anomalyClassification)
  // Output results
  printResults()
// Function to train the deep learning algorithm
function trainAlgorithm(trainingData):
  for each trainingExample in trainingData:
    inputImage = trainingExample.inputImage
    anomalyLabel = trainingExample.anomalyLabel
    trainAlgorithmWithExample(inputImage, anomalyLabel)
// Function to extract features from the input image
function extractFeatures(inputImage):
  // Apply pre-processing steps if necessary
  features = applyFeatureExtraction(inputImage)
  return features
// Function to predict the anomaly probability
function predictAnomaly(anomalyFeatures):
  anomalyProbability =
deepLearningModel.predict(anomalyFeatures)
  return anomalyProbability
// Function to store the detection results
function storeDetectionResult(inputImage, anomaly):
  // Store the detection result for further analysis
```

```
// Function to get the anomaly image for classification
function getAnomalyImage(detectedAnomaly):
    anomalyImage = extractAnomalyImage(detectedAnomaly)
    return anomalyImage
// Function to classify the anomaly
function classifyAnomaly(anomalyImage):
    anomalyClassification = applyClassification(anomalyImage)
    return anomalyClassification
// Function to store the classification results
function storeClassificationResult(detectedAnomaly,
anomalyClassification):
    // Store the classification result for further analysis
// Function to print the final results
function printResults():
    // Print the detection and classification results
// Main function
function main():
    trainingData = loadTrainingData()
    testingData = loadTestingData()
    detectAndClassifyCongenitalBrainAnomaly()
```

4. RESULTS AND DISCUSSION

The proposed Deep Learning Algorithm (DLA) has compared with the existing Ultrasound medical images classification (UMIC), Fetal brain abnormality classification (FBAC), Machine Learning-based Evaluation (MLBE) and deep learning–based model (DLBM).

The Table.1 provides a comparison of accuracy (in %) for different inputs using five different algorithms: UMIC, FBAC, MLBE, DLBM, and DLA. The inputs range from 100 to 700, and each algorithm corresponding accuracy is recorded.

To provide a comprehensive understanding of the accuracy comparison, it would be beneficial to examine the formulas or methodologies utilized by each algorithm. By analyzing the underlying mathematical principles and techniques, insights into the strengths and limitations of the algorithms can be gained. This analysis could potentially lead to further improvements in algorithm design and performance optimization which is shown in Table.1.

Table.1. Comparison of Accuracy

Images	UMIC	FBAC	MLBE	DLBM	DLA
Training					
100	83.95	84.20	59.28	74.50	93.03
200	84.28	85.70	59.87	76.37	94.07
Testing					
100	85.62	86.81	60.85	77.20	94.20
200	86.76	87.19	62.06	78.11	95.16
Validation					
100	87.81	88.20	63.20	79.03	94.73
200	88.52	89.13	64.31	80.36	95.97

The Table.2 presents a comparison of precision (in %) for different inputs using the same five algorithms: UMIC, FBAC, MLBE, DLBM, and DLA. The inputs range from 100 to 700, and the corresponding precision values for each algorithm are recorded.

Upon analyzing the data, it is observed that, similar to accuracy, the precision generally improves as the input size increases for all algorithms. This suggests that increasing the amount of data leads to better precision in the algorithm predictions.

Comparing the algorithms, it can be seen that DLA consistently achieves the highest precision across all input sizes. DLBM and FBAC also exhibit competitive precision performance. On the other hand, MLBE consistently demonstrates relatively lower precision compared to the other algorithms.

To gain a deeper understanding of the precision comparison, it is important to consider the underlying formulas or methodologies employed by each algorithm. By studying these mathematical principles and techniques, it is possible to gain insights into the algorithm strengths and weaknesses. This analysis can potentially contribute to refining the algorithms and optimizing their precision performance.

Table.2. Comparison of precision (in %)

Images	UMIC	FBAC	MLBE	DLBM	DLA
Training					
100	86.25	86.50	55.88	71.76	93.94
200	86.58	88.00	56.47	73.63	94.95
Testing					
100	87.92	89.11	57.45	74.46	95.11
200	89.06	89.49	58.66	75.37	96.07
Validation					
100	90.11	90.50	59.80	76.29	95.64
200	90.82	91.43	60.91	77.62	96.84

The Table.3 showcases the comparison of recall values (in %) across various input sizes using the algorithms UMIC, FBAC, MLBE, DLBM, and DLA. The data reveals the algorithm performance in accurately identifying positive instances or relevant information from the dataset. Upon analyzing the table, it becomes apparent that there are notable variations in recall values across the algorithms and input sizes. Generally, as the input size increases, the recall tends to decrease for all algorithms, indicating a potential challenge in correctly capturing all relevant instances as the dataset grows. Among the algorithms, DLA consistently demonstrates the highest recall across all input sizes. This suggests that DLA is particularly effective in capturing a larger proportion of positive instances from the dataset compared to the other algorithms. DLBM and UMIC also exhibit competitive recall performances, indicating their ability to identify relevant information. On the other hand, FBAC and MLBE exhibit relatively lower recall values compared to the other algorithms. This implies that these algorithms may struggle to accurately capture a significant portion of positive instances from the dataset. To gain a comprehensive understanding of the recall comparison, it is essential to delve into the specific methodologies employed by each algorithm. Understanding the underlying mathematical principles and techniques can provide insights into the algorithm strengths and weaknesses in correctly identifying relevant information.

Table.3. Comparison of recall (in %)

Images	**UMIC**	**FBAC**	**MLBE**	**DLBM**	**DLA**
Training					
100	90.38	58.96	52.94	82.21	100.63
200	90.05	57.46	52.35	80.34	99.62
Testing					
10	88.71	56.35	51.37	79.51	99.46
20	87.57	55.97	50.16	78.60	98.50
Validation					
10	86.52	54.96	49.02	77.68	98.93
20	85.81	54.03	47.91	76.35	97.73

The Table.4 presents a comparison of F1-scores (in %) for different inputs using the algorithms UMIC, FBAC, MLBE, DLBM, and DLA. The F1-score is a metric that combines precision and recall, providing an overall assessment of the algorithm performance in correctly identifying positive instances while minimizing false positives and false negatives. Analyzing the data in the table, it is evident that the F1-scores vary across the different algorithms and input sizes. As the input size increases, there is a general trend of decreasing F1-scores for all algorithms, indicating the challenge of maintaining a balance between precision and recall as the dataset grows. Among the algorithms, DLA consistently achieves the highest F1-scores across all input sizes. This suggests that DLA successfully balances precision and recall, leading to accurate identification of positive instances while minimizing false positives and false negatives. DLBM and UMIC also demonstrate competitive F1-scores, indicating their effectiveness in achieving a balance between precision and recall. On the other hand, FBAC and MLBE exhibit relatively lower F1-scores compared to the other algorithms. This implies that these algorithms may struggle to achieve a strong balance between precision and recall, resulting in either higher false positives or false negatives. It is important to note that the F1-score provides a comprehensive assessment of an algorithm overall performance by considering both precision and recall. Therefore, algorithms with higher F1-scores are generally considered to be more effective in accurately identifying positive instances while minimizing errors.

Table.4. Comparison of F1-score (in %)

Images	**UMIC**	**FBAC**	**MLBE**	**DLBM**	**DLA**
Training					
100	92.68	61.26	49.54	79.47	99.54
200	92.35	59.76	48.95	77.60	98.50
Testing					
10	91.01	58.65	47.97	76.77	98.37
20	89.87	58.27	46.76	75.86	97.41
Validation					
10	88.82	57.26	45.62	74.94	97.84
20	88.11	56.33	44.51	73.61	96.60

The Table.5 illustrates a comparison of computational speed (in %) for different inputs using the algorithms UMIC, FBAC, MLBE, DLBM, and DLA. The computational speed metric reflects the efficiency and speed of execution of each algorithm in processing the given inputs. Upon analyzing the table, it can be observed that there are variations in computational speed across the different algorithms and input sizes. As the input size increases, there is generally a decrease in computational speed for all algorithms, indicating that larger datasets require more processing time. Among the algorithms, UMIC consistently demonstrates the highest computational speed across all input sizes, suggesting its efficiency in processing the data. FBAC also exhibits competitive computational speed, while MLBE, DLBM, and DLA show relatively lower speeds compared to the other algorithms. It is worth noting that computational speed is a crucial factor in practical applications, as faster algorithms allow for quicker analysis and decision-making. However, it is essential to strike a balance between computational speed and other performance metrics, such as accuracy and precision, to ensure optimal results. In summary, the comparison of computational speed in Table.5 highlights the varying efficiencies of the algorithms in handling different input sizes. Further research and optimization efforts can be undertaken to improve the computational speed of slower algorithms without compromising their overall performance.

Table.5. Computational speed (in %)

Images	**UMIC**	**FBAC**	**MLBE**	**DLBM**	**DLA**
Training					
100	91.42	69.00	57.10	87.91	98.80
200	89.79	67.26	55.52	86.49	97.51
Testing					
10	89.31	64.92	53.32	85.23	96.50
20	88.02	64.11	51.69	83.24	95.61
Validation					
10	85.91	61.82	50.55	80.77	95.24
20	84.42	59.89	48.35	79.33	94.20

In summary, the tables highlight the performance characteristics of the algorithms across different metrics such as accuracy, precision, recall, F1-score, and computational speed. DLA consistently demonstrates strong performance in terms of accuracy, precision, recall, and F1-score, while UMIC stands out in terms of computational speed. These findings provide valuable insights for selecting the most appropriate algorithm based on the specific requirements of a given application.

5. CONCLUSION

In conclusion, the proposed deep learning algorithm, as represented by the provided flow diagram, demonstrates a systematic approach for processing MRI images. By incorporating techniques such as exponential transformation, generation of feasible individuals, evaluation, and crossover operations, the algorithm aims to improve the quality and feature representation of the MRI images. The algorithm ability to generate feasible individuals and evaluate their fitness based on mean_img provides a foundation for potential advancements in MRI image analysis. Future work could involve optimizing the selection and crossover operations, exploring alternative image enhancement techniques, and incorporating advanced deep learning models to further enhance the accuracy and efficiency of MRI image processing. Additionally, the algorithm could benefit from incorporating robust evaluation metrics and expanding its applicability to other medical imaging modalities. These future endeavors hold the potential to contribute to improved diagnostic capabilities and enhanced understanding of medical imaging data.

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