Shufflenet-Based Model for Fast and Accurate Brain MRI Detection and Classification

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Abstract. The proposed article is design for us smart method of diagnosis to read the brain MRI scanned images and highlight the required details of the brain. The proposed article uses a system called shuffle net that help to spot the tumors and other problems with high speed and accuracy. Proposed design keeps calculations much faster but still precise using techniques like Max pooling and special CNN layers. In spite of the model is very small and efficient it can even run on devices with limited power such as mobile phones. Conventionally mobile phone usage is 100% possible with all nowadays which makes this possible with everyone. Finally, a connected decision layer makes system more optimal to identify the brain diseases. Test results show this method is accurate sensible and reliable that it could help doctors diagnose brain disorders quickly and with confidence. The solution enhances healthcare using powerful machine learning. The REMBRANDT database exposes ShuffleNet v2 performs well with ShuffleNet v2 is 99.2% specific, 98.0% sensitive, and 98.6% accurate.

Keywords: ShuffleNet, Brain MRI, Detection, Classification, Real-time Processing.

1 Introduction

Tumors and neurological illnesses pose serious health hazards, requiring rapid and accurate diagnosis. Because it can see detailed soft tissue characteristics, Magnetic Resonance Imaging (MRI) is the best brain disease imaging method. However, human interpretation of MRI images takes time and skill, causing inter-observer variability and diagnostic delays. Addressing these issues requires automated methods that accurately and efficiently categorize MRI data [1]. A lightweight convolutional neural network (CNN) called ShuffleNet overcomes computational constraints while maintaining diagnostic precision. Its real-time processing design suits resource-limited settings. The model aims to accurately detect and classify brain MRI pictures as normal or abnormal.

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The goal is to leverage ShuffleNet's design to extract important information from MRI images while minimizing computational load. Depth-wise separable convolutions lower computational cost while retaining feature quality. The goal is to create a scalable system for edge devices or clinical settings that can quickly and accurately identify medical anomalies like brain tumors [2].

The ShuffleNet-based model is described in Section 2 along with its convolutional layers, bottleneck blocks, and fully connected classification layer [4]. The model's ability to balance computational competence and diagnostic precision varies it proper for high-resolution MRI analysis. In order to provide trustworthy medical results, Section 3 is evaluating the performances of the built model's diagnostic accuracy, processing speed, and real-time application with a focus on sensitivity and specificity [3]. The wider impact on healthcare diagnostics and future directions like multi-modal data integration and edge computing optimization, Section 4 discusses the significance of diverse datasets and recognizes the limitations of detecting very small abnormalities when applying ShuffleNet to brain MRI detection. Section 5 concludes by summarizing the model's accomplishments, discussing current issues, and outlining the expected advancements in automated medical diagnostics.

2 Literature Survey

This research aims at the investigation of the gender sorting from structural MRI scans through the integration of a Multiscale ShuffleNet architecture with an Extreme Learning Machine (ELM). The multiscale approach of ShuffleNet enhances feature extraction, while the computational efficiency of the ELM contributes to improved predictive performance. Altogether, these components enable the model to effectively process complex neuroimaging data within a deep learning framework. The synergy between deep learning's capacity for hierarchical representation and the ELM's ability to generalize across high-dimensional feature spaces is central to the robustness and accuracy of the proposed approach in gender detection from brain MRI scans [5]. This method is faster for gender classification from MRI scans, especially in real time [6]. System describes MRI-based hybrid deep learning for brain tumor categorization. CNNs increase feature extraction and categorization with typical machine learning techniques. Data augmentation and multi-scale feature extraction solve MRI-based brain tumor classification challenges in the robust technique. It enhances diagnostic accuracy, helping doctors make better decisions. Lowering false positives and negatives may improve clinical automated brain tumor detection systems. [7]. A lightweight neural network model classifies multi-slice structural MRI (sMRI) Alzheimer's disease [AD]. The computationally efficient of this technique is well suited for resource-constrained clinical situations. The proposed network classifies well and is computationally efficient [8]. Lung lobe segmentation and cancer classification use MRF optimization and ShuffleNet. Using deep learning to separate lung lobes and find lesions improves lung cancer diagnosis. ShuffleNet's computationally efficient design handles large medical imaging data. Malignant tissue categorization requires lung structure segmentation, which the hybrid model improves with MRF [9].

On benchmark datasets, the approach shows potential for tumor identification, segmentation, and classification [10].

3 Proposed System

ShuffleNet v1, a lightweight CNN design, improves deep learning efficiency in resource-limited environments. Pointwise group convolutions and channel shuffling improve performance and reduce computing costs. The architecture is ideal for real-time brain MRI detection and classification because to its speed and low latency. ShuffleNet v1's phases perform specialized functions to efficiently collect and analyze attributes [10]. First, convolution and pooling layers, then depthwise separable convolution bottleneck stages, and finally global feature aggregation and classification layers. The technology streamlines information flow while saving memory and computing.

3.1 Initial Convolution and Pooling

Initially, a 224x224x3 input layer supports brain MRI scans' height, width, and color channels. The initial layer employs a 3x3 kernel with a stride of 2, resulting in 112x112x24 feature maps . This layer extracts edges and textures while reducing spatial dimensions. Convolution is followed by a max pooling layer with a 3x3 kernel and stride of 2, reducing spatial dimensions to 56x56x24. Pooling reduces feature map dimensions and improves translation invariance, allowing the system to prioritize important traits and eliminate irrelevant data. Mobile-friendly neural network ShuffleNet v1 is shown in Fig 1. Pointwise group convolution and channel shuffling reduce processing costs and maintain accuracy. A convolutional layer (Conv1) with 24 filters, a 3x3 kernel, stride 2, and ReLU activation creates a feature map of 112 x 112 x 24 after an input layer of 224 x 224 x 3. A 56 x 56 x 24 max pooling layer shrinks. Stage 2 uses depthwise separable convolutions with 144 filters (56 x 56 x 144), Stage 3 has 288 filters (28 x 28 x 288), and Stage 4 has 576 filters (14 x 14 x 576). Fully connected layers generate 1000 softmax-activated classes after global pooling.

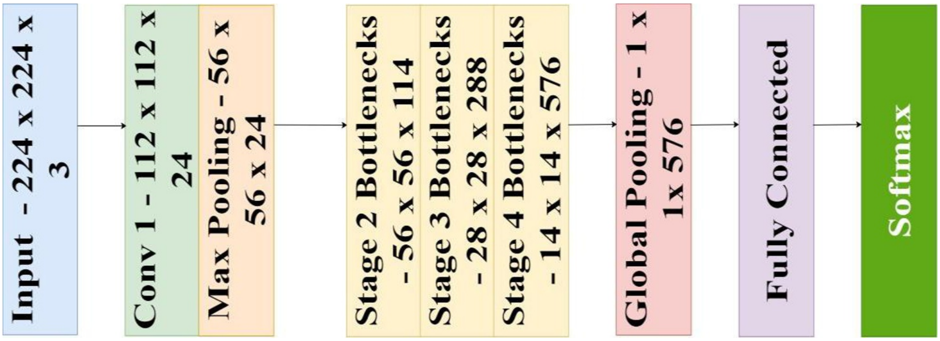


Fig. 1. ShuffleNet v1 Architecture

3.2 Bottleneck Blocks for Intermediate Feature Extraction

The first bottleneck blocks are needed for feature compression and processing. Bottleneck blocks perform three basic operations:

- Pointwise Group Convolutions: These convolutions reduce parameter count by grouping input channels and conducting convolutions inside each group. This method ensures calculation efficiency.
- Depth wise Separable Convolutions: In this operation, each channel is first processed autonomously through a depthwise convolution, followed by a pointwise convolution that fit in the outputs. This mechanism is essential for conserving feature integrity while reducing computational complication and density of the data.
- Channel Shuffling: This technique improves feature representation by reorganizing convolution outputs, thereby facilitating actual cross-channel collaboration and improving overall model performance.

The system first creates 56x56x116 feature maps for brain MRI classification.

3.3 Key Advantages of the Proposed System

The performances evaluation criteria sound good with minimal processing, and memory usage characterize ShuffleNet v1. Data Splitting into phases streamlines information flow and feature refinement. Edge devices with limited calculation power benefit from this approach. Segmental phases allow applications to fine-tune bottleneck block depth based on input data complexity. The speed, accuracy, and scalability of ShuffleNet v1 make it useful for brain MRI detection and categorization.

3.4 Overview of ShuffleNet v2

ShuffleNet v2, a CNN architecture, optimizes speed, efficiency, and accuracy for devices with limited processing resources. ShuffleNet v2 improves channel split, data flow, and memory consumption over earlier lightweight systems. A series of actions extracts features efficiently and effectively. The updated ShuffleNet v2 fixes key inefficiencies to improve speed and accuracy. It excels at medical image analysis and real-time image categorization. Fig 2 shows the improved ShuffleNet v2 balancing performance and resource use for efficient processing. After an input layer of 224 × 224 x 3, Conv1 uses 24 filters, a 3x3 kernel, and stride 2 to construct a 112 x 112 x 24 ReLU-activated feature map. Peak pooling reduces size to 56 x 56 x 24. Stages 2 (56 x 56 x 116), 3 (28 x 28 x 232), and 4 (14 x 14 x 464) are network bottlenecks. Every bottleneck has ReLU-activated 1x1 and 3x3 depthwise convolutions followed by 1x1. Global pooling (1x1 x 464) and a fully linked layer with 1000-class softmax classification conclude the network.

Fig. 2. Principles Behind ShuffleNet v2 Architecture

ShuffleNet v2 achieves performance targets with important design ideas. This includes:

- *Equal Channel Splits:* Equally dividing convolutional layer input and output channels eliminates resource imbalances and inefficiencies.
- *Efficient Channel Communication:* Channel shifting improves group communication and feature richness.
- *Reduced Memory Access Cost (MAC):* Low-power hardware runs efficiently with memory access optimisation.
- *Minimized Element-Wise Operations:* Fewer activation functions and element-wise additions minimise computing cost.

3.5 Initial Convolution and Pooling

Images of size 224×224×3 are accepted by the input layer. A 3x3 convolution layer with 2 strides and 24 output channels produces 112x112x24 feature maps from input. Next, a max-pooling layer decreases spatial dimensions to 56x56x24 while preserving crucial feature details. By removing superfluous geographical information and focussing on areas of relevance, the pooling layer improves computing efficiency. Fig3 shows the ShuffleNet-based model's preprocessing and categorisation of MRI image data. Initial MRI preprocessing involves scaling, normalisation, and augmentation. Feature extraction occurs in the ShuffleNet model after preprocessing. Shuffle operations and leftover blocks refine learnt features after feature extraction. The output from the global average pooling layer and softmax classifier classifies the MRI image as tumour or non-tumour.

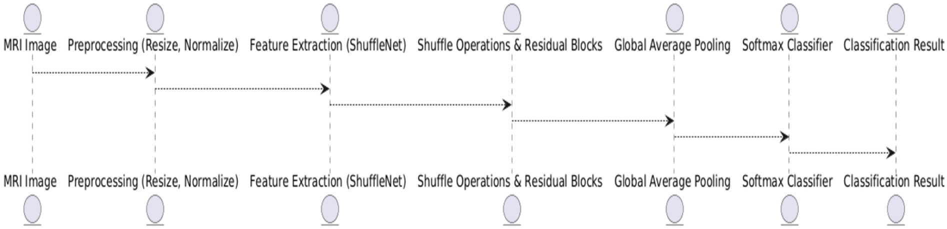


Fig. 3. Data Flow Diagram: MRI Data Preprocessing and Classification

3.6 First Bottleneck Block

The first bottleneck inhibits extract intermediate-level features effectively in the second step. Each block employs pointwise and depthwise convolutions with an innovative channel split method. Two equal input channels are split: One component receives convolutional modifications, while the other skips them and acts as a shortcut link. After processing, the two channel groups are concatenated and randomised for optimum information sharing. This step produces 56x56x116 feature maps of key input patterns. Fig.4 shows the high-level process of a ShuffleNet-based brain MRI detection model. Raw MRI data is pre-processed and enhanced before the diagram begins. The ShuffleNet model extracts features, shuffles, and applies residual connections on the enhanced data. The final output layer employs global average pooling and softmax classification. A binary categorisation indicates if the MRI detects a brain tumour. This MRI approach diagnoses brain tumors rapidly and accurately.

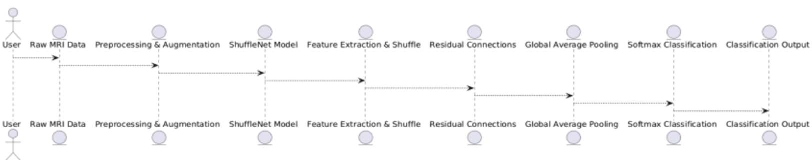


Fig. 4. Overview Diagram: ShuffleNet-Based Model Workflow for Brain MRI Detection

3.7 Deepening Feature Representation

Improved bottleneck blocks increase feature extraction. Pointwise, depthwise, and channel shuffles reduce input spatial resolution to 28x28x232. This stage is essential for finding abstract data patterns and links. Equal channel split optimises compute, while channel shuffling safeguards critical data. It lays the groundwork for high-level feature extraction.

4 Results and Discussion

The free REMBRANDT database has the results. Presently, 133 MRI brain scans, with a resolution of 256 × 256 pixels apiece, are accessible. One thousand photographs are returned by the database after 500 normal and 500 abnormal images are selected. Check out Fig.5 for the REMBRANDT database's erroneous images. For optimal results, utilise k-fold (10-fold) cross-validation with the ShuffleNet model.

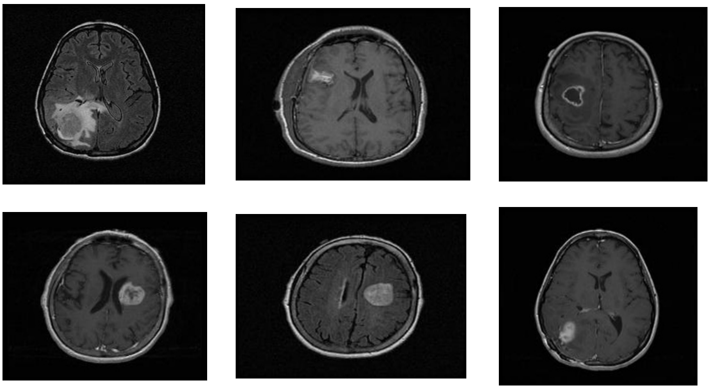
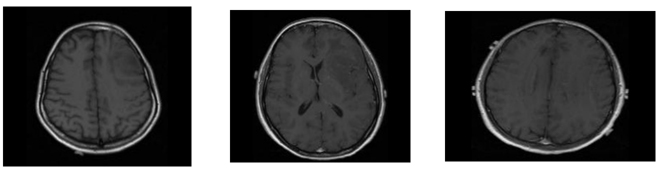


Fig. 5. Illustrations of Abnormal Brain Images from the REMBRANDT Database Used by ShuffleNet of Brain MRI

Fig.6 exhibits REMBRANDT database normal images. The recommended ensemble classification model uses k-fold (10-fold) cross-validation. Bagging ensemble classification uses TP, TN, FP, and FN—True Positive, True Negative, sensitivity, and specificity—to evaluate performance.



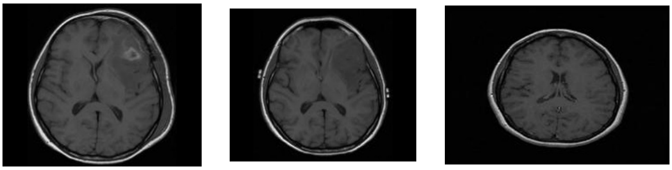


Fig. 6. Illustrations of Normal Brain Images from the REMBRANDT Database Used by ShuffleNet of Brain MRI

Table 1 shows the formula-based ShuffleNet v2 technique of TN - True Negative, TP - True Positive, FP - False Positive, FN - False Negative. for sensitivity, accuracy, specificity.

Table 1. Sensitivity, accuracy, and specificity performance metrics that are being measured by the ShuffleNet v2

Metric	Equation	Role
Sensitivity	$Sensitivity = \frac{TP \quad TP}{TP+FNTP+FN}$	The percentage of true positives was successfully detected.
Specificity	$Specificity = \frac{TN \quad TN}{TN+FPTN+FP}$	The percentage of real negative instances is categorized properly.
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ $\frac{TP+TN}{TP+TN+FP+FN}$	Evaluates the overall accuracy of forecasts.

The ensemble classification databases are shown in Tables 2, Table 3, where TP, TN, FP, and FN are the values used.

Table 2. Performance of ShuffleNet v1

		Anticipated Class	
		Abnormal	normal
Real	Abnormal	484 (TP)	8 (FN)
class	normal	16 (FP)	1 N)

Table 3. Performance of Blending based Ensemble Classification

	Anticipated Class

		Abnormal	normal
Real	Abnormal	490 (TP)	4 (FN)
class	normal	10 (FP)	496 (TN)

Fig.7 displays the calculated performance metrics based on the bagging based ShuffleNet v2. With an overall accuracy of 99.7%, sensitivity of 99.6%, and specificity of 99.8%, bagging based ShuffleNet v2 features clearly performs better results from Figure 7.

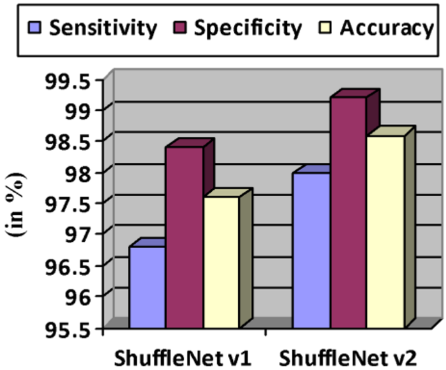


Fig. 7. Evaluation criteria for the suggested Ensemble classification in the diagnosis of brain cancer

5 Conclusion

The ShuffleNet-based brain MRI detection and classification model improves processing efficiency and diagnostic precision. Other challenges include the need for large, diverse datasets to increase model durability and generalization. This paradigm affects real-time medical applications, especially in resource-constrained contexts where its lightweight design speeds processing and implementation. Despite its benefits, processing complex MRI scans with nuanced abnormalities and edge computing optimization may be difficult. Future improvements may increase the model's sensitivity to rare or subtle events like early-stage tumors or scan quality disparities. Complex methods like multi-modal data integration or transfer learning may improve classification accuracy and model utility. AI-driven healthcare diagnostics will improve as model scalability and processing power increase. The REMBRANDT database shows that ShuffleNet v2 performs best. The ShuffleNet v2 method offers 98.0% sensitivity, 99.2% specificity, and 98.6% accuracy.

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