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Bilinear MobileNets for Multi-class Brain Disease Classification Based on Magnetic Resonance Images

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OUTLINE

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Includes research background, research problems, and purpose of the proposed methods

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The materials used, proposed methods, and implementation details

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Conclusion and summary of the proposed research

INTRODUCTION

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RESEARCH BACKGROUND

Brain diseases may cause critical damage to individuals at any age

Early diagnosis is required to deliver further and suitable treatment

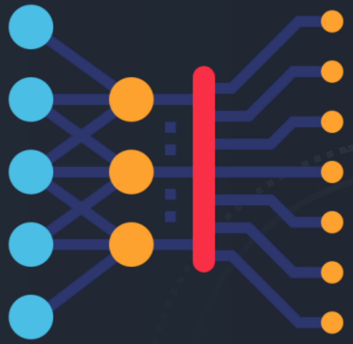
RESEARCH BACKGROUND

MRI is a safe imaging technique for brain disease diagnosis in a non-invasive manner

Clearer images with no radiation

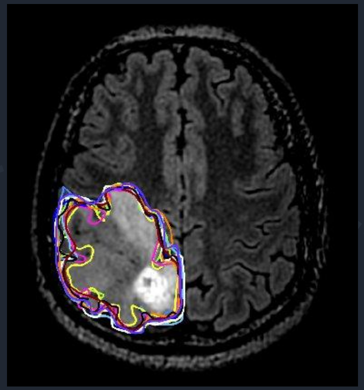
Automated diagnosis research with Machine Learning and Deep Learning

PREVIOUS RESEARCH:
Machine Learning



Machine Learning (i.e. ANN, RF, SVM) based on signal processing approach [1 - 11] (mostly binary)

SVM for multiclass brain disease classification with larger dataset achieved more than 90% accuracy [1 – 2]



https://www.researchgate.net/publication/320900164_On_the_relevance_of_two_manual_tumor_volume_estimation_methods_for_diffuse_low-grade_gliomas/figures?lo=1

Handcrafted feature job in conventional machine learning is time consuming and requires experts

PREVIOUS RESEARCH:
Convolutional Neural Network (CNN)

- Can learn massive numbers of datasets [12]
- Automated feature extraction (fewer preprocessing steps)
- Faster convergence when trained on abundance of data
- Performs better in brain disease classification [12-16]

Gif source: https://programmersought.com/article/917868505/

RESEARCH PROBLEM

Previous Research

- Most studies with both Machine Learning and Deep Learning methods focused on binary classification. However, multi-class classification is crucial for clinical aims.
- CNN obtained better results especially in multi-class brain disease classification[15-16]

Problems

- Important features of brain diseases: location of disease objects, texture, shape, and size of the objects
- The location of the objects may also be diverse between inter-class images
- CNN may take the overall image patterns and ignore the higher-level features such as texture without taking small patches of the object [17]
- When objects are relatively small and appear in clutter, CNN may not give good result (Part-based method may be required)
- Part-based method with handcrafted feature job or creating small patches are more challenging

Solution

- Bilinear MobileNets to improve the classification performance

MATERIALS AND METHODS

The materials used, proposed methods, and implementation details

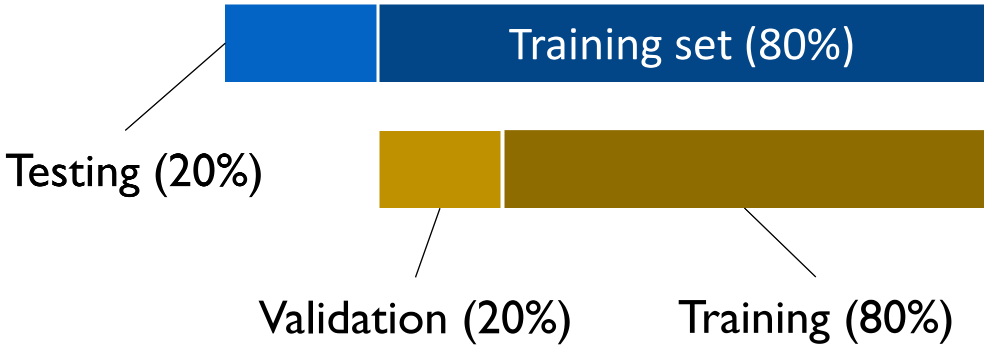
MATERIALS

- A public repository of Harvard Medical School (http://www.med.harvard.edu/AANLIB) provides brain images of all five categories.
- Normal brain taken from IXI Dataset (https://brain-development.org/ixi-dataset)
- Glioblastoma and Low-Grade Glioma tumors were downloaded from the TCIA dataset [19]
- The brain images:
  - 256x256 pixels size
  - Axial T2-weighted MRI
  - RGB images

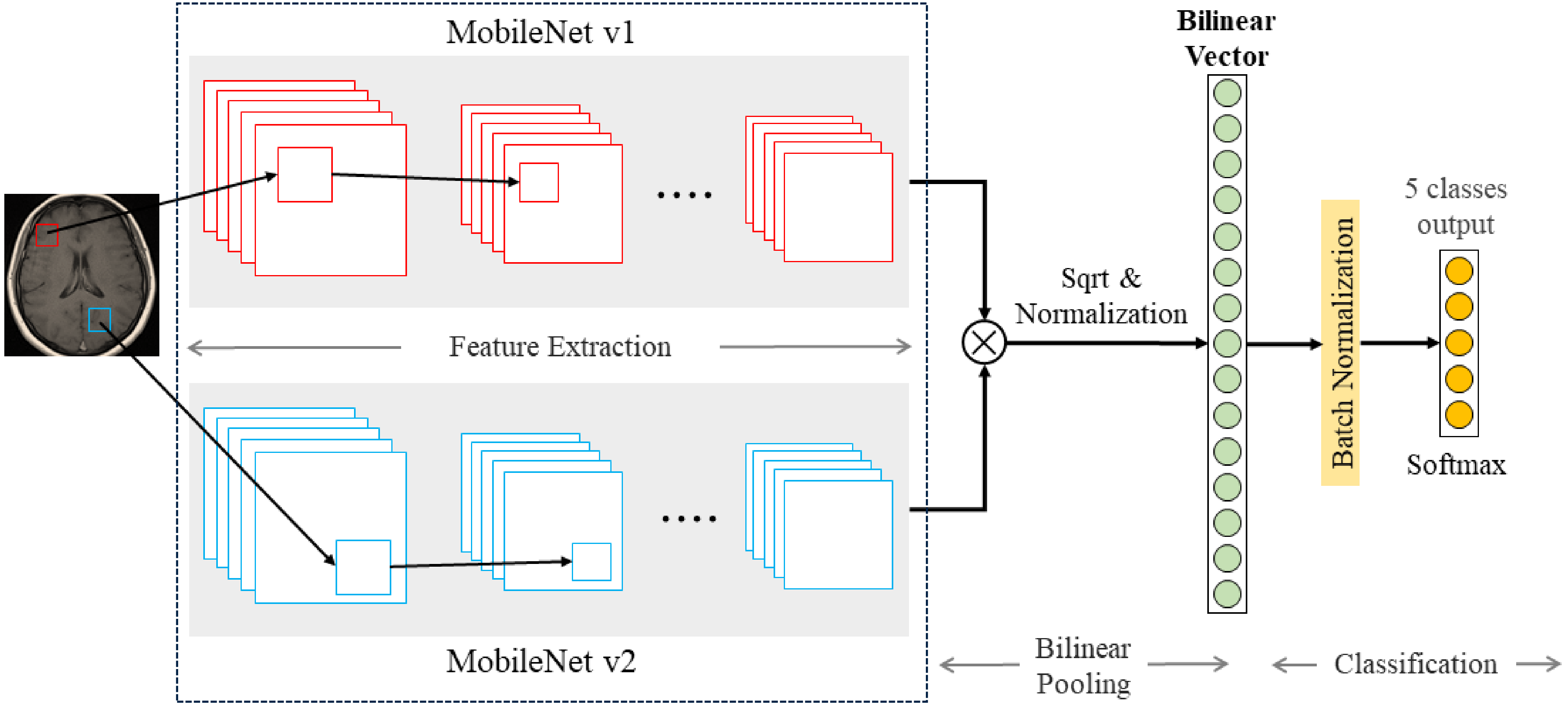
Category	Number of Images
Normal	250
Neoplastic Disease (Brain Tumor)	214
Cerebrovascular Disease (stroke)	315
Degenerative Disease	116
Inflammatory / Infectious Disease	135
Total	**1030**

DATA PREPROCESSING

- Resize images from (256, 256, 3) to (224, 224, 3)
- Split into training, validation, and testing set
- By applying the data splitting, each of the train, validation, and test sets are settled with 485, 122, and 152 images, respectively.



PROPOSED ARCHITECTURE



via Transfer learning

IMPLEMENTATION DETAIL: REALTIME AUGMENTATION

Applied augmentation techniques to tackle imbalanced data problems

Augmentation Technique	Values
Rotation range	10-20 degree
Zoom range	0.1-0.3
Width shift range	0.03
Height shift range	0.03
Horizontal flip	True

IMPLEMENTATION DETAIL: HYPERPARAMETER EVALUATION

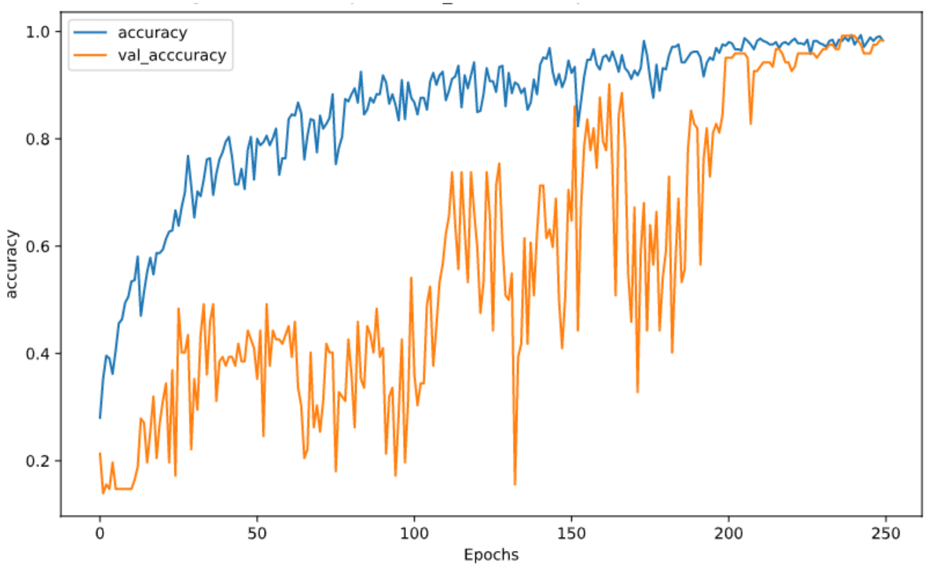
Different architectures and hyperparameters evaluated before reaching the final model

Parameters	Values
Optimizer	Stochastic Gradient Descent (SGD)
SGD Nesterov	True
SGD Momentum	0.1, 0.2, 0.5
Initial learning rate	0.01, 0.1
Batch Size	32
Loss Function	Categorical Crossentropy
Epoch	100, 250, 500

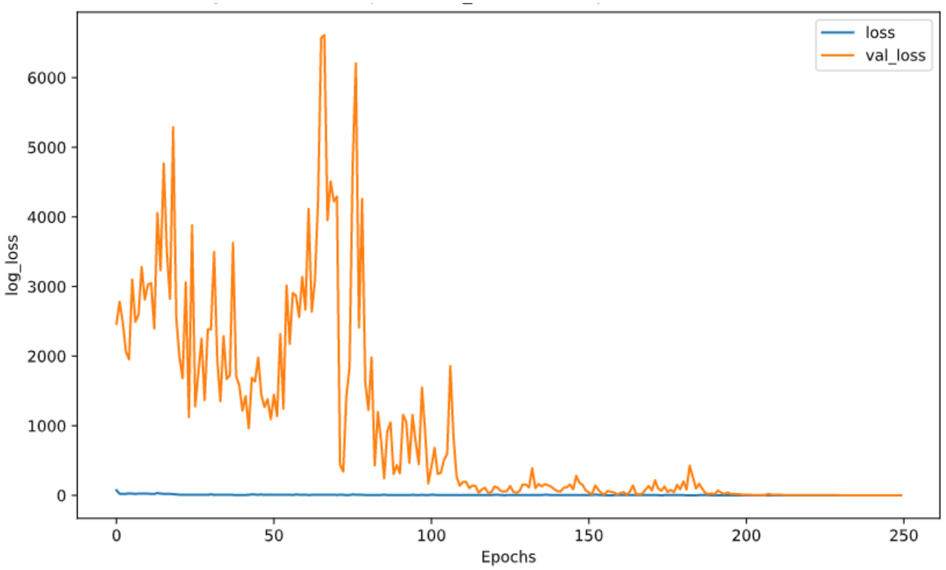
EXPERIMENTS AND RESULTS

Experimental results of the proposed methods

TRAINING RESULTS



Training and validation accuracy

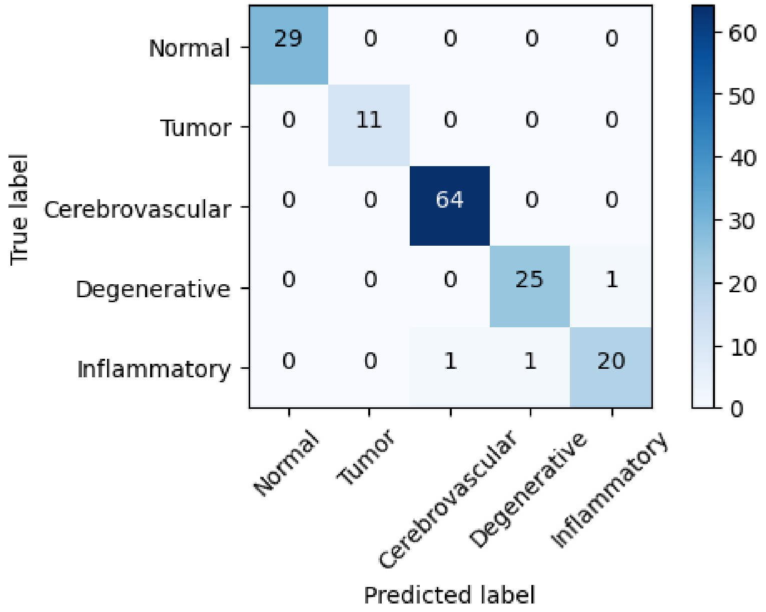


Training and validation loss

TESTING RESULTS

Testing results for multi-class brain disease classification using Bilinear MobileNets

	Precision (%)	Recall (%)	F1-score (%)	Support
Normal	100	100	100	29
Tumor	100	100	100	11
Cerebrovascular	98.46	100	99.22	64
Degenerative	96.15	96.15	96.15	26
Inflammatory	95.24	90.91	93.02	22
Accuracy			**98.03**	152
Weighted avg	**98.01**	**98.03**	98.01	152



Confussion matrix of the Bilinear MobileNets

PERFORMANCE COMPARISON

	Acc (%)	Model	No of classes	No of images	No of param (mil)
(Siddiqui et al., 2017) [1]	95.70	KNN+ RF + LS-SVM	6	310	-
(Gudigar et al., 2019) [2]	90.68	VMD + SVM	5	612	-
(Talo, et al., 2019) [15]	95.23	CNN (ResNet50)	5	1074	~25
(Nayak et al., 2020) [16]	97.50	Deep CNN	5	200	0.25
Bilinear MobileNets (proposed)	**98.03**	CNN	5	1030	17

TOOLS

- Computer device: with Intel Core i7-9750H CPU, 40-GB RAM, and NVIDIA Geforce RTX 2060 6GB GDDR6 GPU.
- Open-source Deep Learning framework Tensorflow with Keras library on Python
- The training time: 2571 seconds for 485 images
- Testing time: 160 milliseconds for 152 images or 1.05 milliseconds for each image

CONCLUSION

Conclusion and summary of the proposed research

Conclusion

- This paper proposed a bilinear method by employing MobileNetV1 and MobileNetV2 as backbone networks via transfer learning to classify MR images into five classes
- This study has used more extensive data compared to most previous studies
- Real-time data augmentation was also implemented in this study to tackle the imbalance data problem
- The proposed model increases the accuracy up to 98.03% when evaluated on the untouched dataset
- The proposed model has lighter parameters compared to a single Deep CNN model like ResNet50, but still maintained to perform better accuracy

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THANK YOU.