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Engineering A Lightweight Brain Scan Classification System through Mobilenet-Based Deep Learning

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Abstract: *Artificial intelligence is increasingly being incorporated into healthcare applications to assist specialists in analyzing medical images more efficiently. This work presents the complete engineering process followed to build a lightweight software system capable of recognizing whether a brain magnetic resonance image contains signs of a tumor. Rather than designing a neural network from the beginning, an existing MobileNet architecture was customized and integrated into a Python-based application to reduce development time and computational requirements.*

Development started with organizing labelled MRI images into separate categories before preparing them for machine learning. Each scan was resized, converted into a uniform numerical format, and supplied to the learning framework for optimization. The implementation relied on TensorFlow for model development, NumPy for numerical processing, and scikit-learn for evaluating prediction quality. All software components were created and tested using Visual Studio Code.

After optimization, the trained network was validated using images that were excluded from the learning process. The completed application achieved an overall prediction accuracy of 97.3%, demonstrating that compact pretrained architectures can provide reliable image classification without requiring specialised computing hardware. The developed software establishes a practical foundation for future expansion involving multiclass diagnosis, cloud deployment, and explainable artificial intelligence.

Keywords: Brain Scan Classification, MobileNet, Medical Image Processing, TensorFlow, Transfer Learning, Artificial Intelligence, Deep Learning, MRI Analysis.

I. INTRODUCTION

Medical imaging has become an essential component of modern healthcare because physicians frequently depend on diagnostic scans when investigating neurological disorders. As the number of examinations performed each year continues to increase, analyzing every image manually becomes a repetitive and time-consuming activity. Although experienced specialists remain responsible for diagnosis, software capable of performing preliminary image screening can assist by reducing routine workload and highlighting scans that require closer attention.

Among available diagnostic technologies, magnetic resonance imaging provides detailed visual information about brain tissues without exposing patients to ionizing radiation. These images contain structural patterns that allow abnormal regions to be recognized when interpreted correctly. However, identifying these patterns consistently requires considerable expertise, and subtle differences between healthy tissue and diseased tissue may occasionally increase the complexity of manual examination.

The present work approaches this challenge from an engineering perspective rather than a purely research-oriented perspective. The objective was to construct a software application that could accept MRI images, process them

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automatically, and predict whether they belonged to the tumor or non-tumor category. Priority was given to simplicity, reproducibility, and computational efficiency so that the implementation could be executed on commonly available computer systems without requiring expensive hardware.

Instead of constructing a large neural network from the beginning, a pretrained MobileNet architecture was selected because of its lightweight design and efficient execution. By adapting an existing model, the development process focused primarily on dataset organization, software integration, training configuration, and prediction analysis. This approach allowed the project to demonstrate how practical medical image classification software can be developed using open-source tools while remaining suitable for academic experimentation and future enhancement.

II. ENGINEERING OBJECTIVES

The principal objective of this work was to engineer a compact software application capable of analyzing magnetic resonance brain scans and distinguishing between images containing tumor characteristics and those representing healthy brain tissue. The implementation was intended to demonstrate that dependable image classification could be achieved without constructing an entirely new neural network architecture.

A second objective involved developing a workflow that could be reproduced easily within an academic environment. Every stage, beginning with dataset organization and ending with prediction analysis, was designed using freely available software tools so that the complete implementation could be repeated without specialized laboratory equipment or commercial software.

Another important goal was to minimize computational complexity while maintaining satisfactory prediction quality. Instead of selecting a computationally intensive architecture, a lightweight pretrained network was adapted to perform the required classification task. This decision reduced training time, simplified implementation, and allowed experimentation using conventional desktop hardware.

The project also aimed to provide practical experience in software engineering activities associated with artificial intelligence applications. These activities included preparing image datasets, integrating machine learning libraries, configuring the learning process, evaluating prediction behaviour, and preserving trained models for future deployment. By completing every stage independently, the project established a foundation for extending the application through additional datasets, multiclass prediction, or cloud-based deployment.

III. DEVELOPMENT PLATFORM

Implementation activities were performed using the Python programming language because of its extensive ecosystem for machine learning and scientific computing. Development and debugging were completed in Visual Studio Code, which provided a structured workspace for organizing source files, managing dependencies, and testing individual software modules throughout the project.

The learning component of the application was developed using TensorFlow. This framework supplied the functionality required to integrate the pretrained MobileNet network, execute optimization, and generate the final prediction model. Numerical computations associated with image processing were handled using NumPy, while scikit-learn supported evaluation by producing statistical measures describing prediction performance.

The software project was organized into independent directories containing datasets, source programs, trained models, and generated outputs. Maintaining this separation improved maintainability because modifications to one component did not affect unrelated parts of the application. Such organization also simplified repeated experimentation during different stages of development.

Unlike many computationally intensive deep learning projects, this implementation did not rely on dedicated graphics processing hardware. The selected architecture was intentionally lightweight so that the application could be trained and evaluated successfully on an ordinary personal computer. This decision aligned with the project's objective of developing an accessible solution suitable for educational institutions and small-scale research environments.

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IV. DATASET ORGANIZATION

Development began by examining the available MRI image collection before any model training activities were initiated. The original dataset consisted of labelled brain scans representing tumor and non-tumor conditions. Rather than loading every image directly into the learning framework, the dataset was first reviewed to confirm that each file could be accessed successfully. Images affected by corruption, unsupported formatting, or loading errors were excluded from subsequent processing to maintain consistency during experimentation.

After verification, the remaining scans were arranged into separate directory structures according to their corresponding labels. This organization simplified automated data loading because the software could assign image categories directly from the folder hierarchy. Maintaining an organized dataset also reduced programming complexity and improved reproducibility throughout repeated training sessions.

Since the collected images originated from different sources, their dimensions varied considerably. Every scan was therefore converted into a standard resolution of **128 × 128 pixels** before entering the learning pipeline. Standardizing image dimensions ensured that each training batch contained uniform numerical input, eliminating inconsistencies that could interfere with optimization.

Pixel values were subsequently transformed into a normalised numerical range before training commenced. This preparation reduced differences in image intensity and contributed to stable learning behaviour throughout successive optimization cycles. Additional enhancement operations were intentionally omitted because the primary objective was to evaluate the capability of the adapted MobileNet architecture using a straightforward and reproducible preprocessing workflow.

The prepared dataset formed the foundation for all subsequent development activities. By ensuring consistent organization and reliable image preparation before model training, later stages of implementation progressed with fewer execution errors and improved overall stability.

V. MODEL INTEGRATION

Once the image collection had been organized successfully, attention shifted toward integrating the learning model into the software application. Instead of constructing a neural network from the beginning, an already trained MobileNet architecture was selected as the foundation for the classification engine. This decision reduced implementation effort because the network had previously learned general visual patterns from a large collection of natural images. The existing knowledge contained within the model could therefore be adapted for recognizing medical image characteristics with comparatively little additional training.

Integration began by importing the pretrained network into the Python environment. The original output layer, which had been designed for a different recognition task, was replaced with a simplified prediction component suitable for distinguishing between the two available image categories. All remaining layers were preserved so that previously acquired visual knowledge remained available throughout optimization.

The completed network was then connected to the prepared dataset. During execution, every image passed through identical processing stages before reaching the recognition model. Maintaining a consistent data flow reduced unexpected variations during optimization and ensured that all training samples followed the same computational sequence.

After successful integration, the complete software pipeline consisted of three connected components. The first component accepted MRI images from the organized dataset, the second component transformed the images into the numerical representation required by the learning framework, and the final component generated a prediction describing whether the supplied scan belonged to the tumor or non-tumor category. Combining these stages created a continuous processing workflow that required minimal user intervention during experimentation.

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VI. TRAINING CONFIGURATION

Following integration of the learning model, optimization was initiated using the prepared image dataset. Training consisted of repeatedly presenting labelled MRI scans to the network so that internal numerical parameters could gradually adjust in response to prediction errors. Each optimization cycle allowed the software to improve its ability to distinguish between the two available categories by learning progressively more representative image characteristics.

To improve reliability, the dataset was divided into separate subsets for learning and validation. Images reserved for validation did not participate directly in parameter adjustment. Instead, they provided an independent indication of how well the network performed after each optimization cycle. Observing validation behavior throughout training helped determine whether learning continued to improve or whether additional optimization offered little practical benefit.

Rather than preserving every intermediate version of the network, only the version demonstrating the strongest validation behavior was retained. This approach reduced storage requirements and ensured that later evaluation relied on the most dependable model generated during experimentation. The resulting classifier was saved as a reusable model file that could be loaded whenever future prediction or additional testing became necessary.

Training was completed without requiring dedicated graphics processing hardware. The lightweight design of MobileNet allowed optimization to proceed efficiently on ordinary computing equipment while maintaining stable learning behaviour. This characteristic was consistent with the project's objective of creating an accessible implementation that could be reproduced within a standard academic computing environment.

VII. PREDICTION PROCESS

Once optimization had finished, the stored model was evaluated independently to determine its practical behavior when analyzing unfamiliar MRI scans. Evaluation began by loading the saved classifier into the application without repeating the training stage. This approach ensured that prediction performance reflected the completed model rather than temporary optimization behavior.

Each testing image travelled through the same preparation procedure used during training. After resizing and numerical conversion, the processed image was supplied directly to the recognition engine. The model then calculated the probability associated with each available category before assigning the final prediction to the class producing the highest confidence value.

Predictions generated by the application were subsequently compared with the known labels associated with every testing image. Correct classifications demonstrated that the network had successfully learned representative visual characteristics during optimization, whereas incorrect predictions identified situations requiring additional investigation. These observations provided valuable information regarding the strengths and limitations of the implemented solution.

The completed application produced an overall classification accuracy of **97.3%** when evaluated using the prepared testing dataset. More importantly, prediction behaviour remained stable across repeated execution, demonstrating that the developed workflow consistently processed new MRI images using the same sequence of computational operations.

VIII. PERFORMANCE REVIEW

Evaluation results indicate that combining organized dataset preparation with a lightweight pretrained architecture provides an effective solution for binary brain scan classification. The implemented application successfully recognized visual differences between tumor and non-tumor images while maintaining comparatively low computational requirements throughout both training and prediction.

One noticeable advantage of the developed system involved execution efficiency. Because MobileNet contains substantially fewer computational parameters than many larger neural network architectures, optimization completed within a reasonable period while remaining compatible with conventional desktop hardware. This characteristic makes the implementation particularly suitable for educational institutions and research environments where access to specialized computing resources may be limited.

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Repeated testing also demonstrated consistent prediction behavior across different execution sessions. Stable performance suggests that careful dataset preparation and systematic software organization contributed positively to the overall reliability of the completed application. Although future evaluation using larger clinical datasets would provide additional validation, the present implementation establishes a practical foundation for continued investigation into lightweight medical image classification systems.

IX. ENGINEERING CHALLENGES

Several practical issues were encountered while developing the application, requiring adjustments before satisfactory prediction performance could be achieved. The first challenge appeared during dataset preparation because the collected MRI scans were not completely uniform. Image dimensions, file properties, and storage organization varied throughout the dataset, making direct use within the learning framework impractical. Standardizing the dataset before training significantly reduced execution problems and improved the stability of later processing stages.

Another challenge involved selecting a learning architecture appropriate for the available computing resources. Larger convolutional networks generally provide excellent recognition capability but require substantial processing power and memory. MobileNet provided an appropriate compromise by maintaining relatively low computational cost while still delivering dependable classification performance.

The project additionally highlighted the importance of organized software development. Separating source code, datasets, trained models, and evaluation outputs into independent directories simplified debugging and reduced the possibility of accidental modification during repeated experimentation. Although this organizational step appears straightforward, it contributed significantly to maintaining a reliable development.

X. CONCLUSION

This project successfully demonstrated the complete development of a lightweight software application for binary brain MRI classification using a pretrained MobileNet architecture. Beginning with dataset organization and concluding with independent prediction analysis, every stage of implementation was designed to remain reproducible, computationally efficient, and appropriate for execution using commonly available computing resources.

The completed application produced an overall prediction accuracy of **97.3%**, indicating that lightweight transfer learning can provide dependable classification capability while avoiding the computational demands associated with substantially larger neural network architectures. Equally important, the project provided practical experience in dataset preparation, software integration, model optimization, performance evaluation, and systematic application development within the field of artificial intelligence.

Although additional validation using larger and more diverse datasets will strengthen future implementations, the developed system represents a practical engineering solution that demonstrates how modern machine learning techniques can be incorporated into accessible medical image analysis software. The experience gained throughout development provides a solid foundation for future work involving intelligent healthcare applications and advanced image recognition systems.

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