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**Brain Tumor Classification using deep Learning Techniques**

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**Module Code: CIS4050-N**

**Module Title**

**Deep Learning**

**Assignment Title**

**Individual Report (Element 2)**

**Degree of Masters (Msc) in Applied Artificial Intelligence**

**Critical Review of the Scientific Paper**

**Title**: **Brain tumor classification using deep learning techniques: a systematic literature review**

### What is the main problem/research question in the paper? Why is the problem significant?

### ****Main Problem / Research Question and Its Significance:****

The central research question of the paper is: **How effective are deep learning techniques in the classification of brain tumors using medical imaging, particularly MRI scans?** The paper explores this question by conducting a comprehensive systematic literature review of existing deep learning-based approaches applied to brain tumor classification.

The significance of this problem is immense in the field of medical diagnostics. Brain tumors, if not diagnosed and treated early, can be life-threatening. Accurate classification plays a crucial role in determining the treatment path and prognosis. Traditionally, classification is done manually by radiologists, which is time-consuming, subjective, and prone to error due to fatigue or human bias. In this context, the automation of tumor classification using deep learning is vital as it can improve diagnostic accuracy, speed, and consistency. The research question is therefore both timely and aligned with current global efforts in medical AI to assist clinical decision-making.

1. **What are the main findings/results?**

**Main Findings / Results:**

The review synthesizes findings from 46 high-quality publications between 2016 and 2023. It concludes that **Convolution Neural Networks (CNNs)** are the most widely adopted and effective models for brain tumor classification, often outperforming traditional machine learning methods due to their ability to automatically learn hierarchical features from raw image data.

The review further notes the growing adoption of **transfer learning models**, such as **ResNet**, **VGGNet**, and **Inception**, which are especially useful when dealing with small medical datasets. Additionally, **hybrid models** combining CNNs with RNNs or LSTM architectures have shown promise in improving classification accuracy.

Reported results from various studies consistently show high accuracy (often above 90%), particularly when deep learning models are trained with augmented data, preprocessed scans, and fine-tuned hyperparameters. The review highlights that the choice of architecture, data preprocessing, and evaluation metrics plays a critical role in model success.

1. **What data was used? What methodology was used? What experiments were carried out?**

### ****Data, Methodology, and Experiments:****

The paper itself is a **systematic literature review** and does not include original experiments. Instead, it analyzes previous studies using structured inclusion/exclusion criteria. The datasets commonly used in the reviewed studies include:

* Kaggle brain tumor datasets

These datasets generally consist of **T1-weighted or T2-weighted MRI images**, sometimes annotated for tumor types such as glioma, meningioma, and pituitary tumors.

The **methodology** of the review includes:

* Identification and collection of studies from databases such as Scopus, IEEE Explore, Pub Med, and Science Direct.
* Filtering based on relevance, publication date, and methodological rigor.
* Analysis based on deep learning architecture, dataset size, preprocessing techniques, evaluation metrics, and performance.

Many of the reviewed studies use traditional CNNs as baseline models. Others utilize **pre-trained models** such as **ResNet50** and **Efficient Net**, applying **transfer learning** to improve model performance on small datasets. Models are typically evaluated using metrics such as **accuracy, precision, recall, F1-score, and ROC-AUC**.

In our group project, we applied three models—**ResNet50, EfficientNetB0, and a custom CNN**—which directly align with the paper’s emphasis on deep CNN architectures and transfer learning strategies.

1. **What are the interpretations of the results? Do the results support the conclusions  
   drawn in the paper? What are the limitations/constraints/assumptions?**

### ****Interpretation of Results, Conclusions, and Limitations****

The authors interpret the reviewed findings to mean that **deep learning is a reliable and high-performing approach** to brain tumor classification, with strong generalizability when models are properly trained. They highlight that CNN-based architectures can automatically extract complex features from medical images that may not be obvious to human radiologists.

The results support the paper’s conclusions that:

* Deep learning models are increasingly effective and outperform traditional methods.
* Transfer learning enhances performance, especially when dealing with small or imbalanced datasets.
* Data augmentation and preprocessing are essential for reliable performance.

However, the paper acknowledges several **limitations and constraints**, including:

* **Limited dataset availability**, which restricts generalizability.
* **Lack of model explain ability**, making clinical adoption difficult.
* **Over fitting issues** in small datasets if not handled with care.
* **Lack of standardization** in datasets, preprocessing, and evaluation.

While the conclusions are well-supported, the paper could have included a deeper discussion on **ethical concerns, model bias, and interpretability tools** like Grad-CAM or SHAP, which are essential for real-world deployment in clinical settings.

1. **Are there any comparisons with previous work?**

### ****Comparison with Previous Work****

The paper compares deep learning models with **traditional machine learning approaches** such as SVM, Random Forest, and k-NN. It finds that while traditional models rely on handcrafted features and often require extensive domain expertise, deep learning models can learn complex patterns directly from image data.

In particular, the paper shows how models like **ResNet and Inception** offer significant improvements in accuracy over traditional methods, particularly when transfer learning is used. It also references improvements in training time and model convergence through the use of pre-trained models.

Our group project extends this analysis by applying **EfficientNetB0**, a more recent architecture that balances model complexity with accuracy. This helps to illustrate how newer models continue to build on the foundational CNN architecture and outperform older baselines.

1. **How do you relate the paper with your ideas and views? Are the arguments logical?  
   What other directions could have been explored?**

### ****Relation to Our Project, Ideas, and Future Directions****

This paper directly influenced our group project. We took inspiration from the findings and applied three different models to classify brain tumors from MRI images:

* **CNN** as a baseline model
* **ResNet50** for transfer learning with moderate depth
* **EfficientNetB0** for lightweight but high-performance modeling

The paper validated our choice of architectures and inspired our focus on **data preprocessing**, **augmentation**, and **model evaluation**. Our experiments further reinforced the idea that **transfer learning models** significantly outperform custom CNNs on small datasets.

The arguments in the paper are well-structured and supported by quantitative evidence. However, we felt that the review could have explored more **real-world deployment aspects**, such as integrating explain ability tools or comparing model performance across diverse patient populations.

In our project, we also explored **Grad-CAM visualizations** to understand what parts of the MRI scans the models focused on, something the paper only briefly mentioned. This helped us make our model outputs more transparent and clinically interpretable.

For future directions, the paper could explore:

* **Federated learning** for privacy-preserving training across hospitals
* **Multi-modal data fusion**, combining imaging with patient history
* **Explainable AI (XAI)** frameworks to gain clinical trust
* **Benchmarking with synthetic datasets** for data-scarce environments

### ****Conclusion:****

Overall, the scientific paper provides a solid foundation for understanding the application of deep learning in brain tumor classification. It is highly relevant to our group project, both in its technical content and in the challenges it highlights. The paper effectively synthesizes years of research and presents a strong case for the use of CNN-based deep learning models in medical imaging.

By building upon its insights and applying newer architectures like EfficientNetB0, our group project bridges the gap between literature and practical implementation. The alignment between the reviewed work and our experiments not only validates our approach but also demonstrates our ability to critically apply academic research in real-world scenarios.

**Reflective writing: Contribution to group project**

**Group work observation:**Our group project focused on classifying brain tumors using deep learning models. The aim was to evaluate and compare different architectures for their effectiveness in classifying tumors from MRI images. I was primarily responsible for implementing the foundational base models, which served as the starting point for further tuning and performance analysis.

**Individual Contributions:**

My key contribution was the implementation and evaluation of the core deep learning model. I began by developing a custom CNN as our base line. Building on that, I implemented more advanced architecture including ResaNet-50, EfficientNetB0, and DensNet-121. Each model required careful design, including configures layers, activation functions, optimizer and of training parameters.  
  
I conducted the preliminary test, adjusted hyper parameters such as the learning rate and batch size, and applied regularization techniques such as dropouts and data augmentation to avoid over fitting. These foundational models were later fine tuned by Snehal kumar Patel for improved performance. Connor managed the data preprocessing pipeline, handling image resizing, normalization and dataset splitting.

**Reflection on Challenges and Successes:**

One challenge I encountered was balancing model complexity with computational efficiency. While models like Resnet-50 and DENSENET-121 offer high accuracy, they were resource-intensive and slow train. EfficnetB0, on the other hand, provided a good trade-off between accuracy and computational load. It was important to evaluate models not only on performance metrics but also on feasibility for deployment.

Overall, our approach proved successful. We achieved strong classification performance, particularly with ResNet-50 and EfficintNetB0. The iterative testing and refining process helped us identify the best suited models for our dataset and objectives.

**Lessons Learned:**

This project deepened my understanding of deep learning model development. I learned that model performance is influenced by more than just architecture - preprocessing, data augmentation, and tuning strategies all play vital roles. I also recognized the need to experiment with multiple architectures rather than relying on a size-fits-all model.  
  
Another major takeaway was the value of teamwork. Each member brought a unique skill set to the project. Our open communication and collaborative problems enabled us to overcome challenges and improve our final output.  
  
Looking ahead, I plan to continue experimentation with advanced architecture and focus more on hyper parameter tuning and model interpretability. I also aim to strengthen my collaboration skills, as team input was instrumental in refining our models.