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An Integrating CNN and Texture Features for Enhanced Brain Tumor Diagnosis from MRI Scans

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Abstract-Using T1-weighted contrast-enhanced MRI scans, this paper offers a hybrid model combining deep convolutional features from ResNet50 with manually created texture descriptors for brain tumour classification. Three tumour kinds in the dataset are meningioma, glioma, and pituitary. Steps in preprocessing include converting photos to greyscale, applying median filtering to lower noise, downsizing to a consistent input size, normalising pixel values, and doing data augmentation to increase generalisation. The model's backbone is ResNet50, a pretrained deep convolutional neural network that uses residual learning to retrieve high-level features. At the same time, Gabor filters and the Gray-Level Co-occurrence Matrix (GLCM) are used to extract manually created texture characteristics, which records spatial connections of pixel intensity. Haralick features are generated from GLCM to measure texture patterns, hence complementing deep features. The hybrid model has a dual-branch architecture: one branch handles GLCM-based descriptors, while the other processes ResNet50-derived features. Final classification results from passing these features through fully linked layers with dropout for regularisation and concatenation. By way of contrast, GLCM characteristics alone train conventional machine learning classifiers like Support Vector Machine (SVM) and K-Nearest Neighbours (KNN). To keep balanced class representation, the dataset is divided using an 80:20 stratified train-test split. Model performance is measured and compared using evaluation criteria including accuracy, precision, recall, F1-score, and ROC-AUC. The findings reveal that integrating deep and handmade characteristics improves classification accuracy, hence highlighting the use of hybrid techniques for brain tumour identification from MRI pictures.

Keywords- Brain Tumor Classification, Hybrid Model, Machine learning, Deep learning and MRI Image Analysis

I. INTRODUCTION

Abnormal cell growths inside the brain or surrounding tissues, brain tumours are among the most major health issues globally. These tumours fall into benign or malignant categories, each of which calls for different medical therapies. Proper therapy depends on timely and precise detection; hence, it helps to raise survival rates.[1]. Without early discovery, benign tumours could develop unnoticed; malignant tumours could spread fast, therefore complicating and weakening treatment. Traditionally, brain tumour diagnosis combines clinical evaluations and imaging modalities, with an MRI being the most often utilised tool. Though reading these pictures might be difficult and time-consuming, MRI offers clear brain imaging.[2]. To

properly identify and categorise the tumour kind, radiologists have to sift through vast amounts of images, which can cause diagnosis delays and raise the risk of human mistake.

Machine learning (ML) in addition to deep learning (DL) methods have attracted great attention in the healthcare sector to meet these difficulties, especially for medical picture processing.[3]. By automating the examination and analysis procedure, these computational methods are changing brain tumour categorisation. Widely utilised to extract pertinent information from MRI scans and categorise the tumours as benign or malignant are machine learning algorithms such as supported vector machines (SVM), k-nearest neighbours (KNN), and decision trees.[4]. Deep learning techniques, especially computational neural networks (CNNs), have on the other hand shown to be rather successful in learning hierarchical patterns from the photos. By means of CNNs, classification accuracy is greatly enhanced and human participation is lowered by means of identification of minute characteristics and patterns that may elude conventional methods.

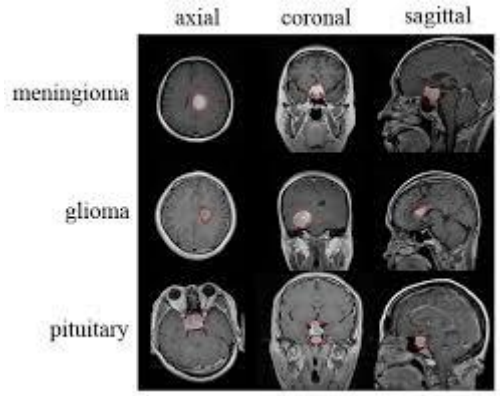

Fig.1 Brain Tumor Classification

The preprocessing of medical pictures is crucial in the tumour grouping pathway. [5]. Before being input into AI or deep learning models, techniques such as image enhancement, reduction of noise, and feature extraction help to guarantee that the pictures are of the best quality. These algorithms then classify tumours and examine the aspects[6]. Particularly strong is the mix of neural networks and deep learning methods since it enables automatic learning from large datasets, hence lowering manual effort and improving accuracy.[7]. These strategies can result in quicker and more precise diagnoses, hence enhancing patient care and results by means of greatly lowering the burden on medical workers. [8]. The prospective of brain tumour categorisation is quite promising as these technologies develop since it may be used in personalised therapy, early identification, and more efficient treatments catered to particular patient needs.

II. Literature Review

Md. Monirul Islam (2023) et al This study intends to investigate how well deep transfer learning architectures work for brain tumour diagnosis. This work uses four transfer learning architectures: MobileNet, DenseNet121, VGG19, and InceptionV3. To validate the models, we employed a dataset comprising data from three benchmark databases: figshare, SARTAJ, and Br35H. There are four categories in these databases: pituitary, no tumour, meningioma, and glioma. Image augmentation helps to balance the classes.[9].

Gopal S. Tandel (2023) et al To maximise the classification capacity between low-grade versus high-grade glioma, three datasets were created consisting of three MRI sequences: T1-Weighted (T1W), T2-weighted (T2W), or fluid-attenuated inversion recovery (FLAIR). Moreover, tumour classification was done using five well-known convolutional neural networks: AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50.[10].

Jian Wang (2024) et al Manual interpretation of brain MRI is error-prone depending mostly on empirical experience and the radiologists' fatigue level. Because they can offer precise prediction outcomes based on medical images using cutting edge computer vision technologies, computer-aided diagnostic (CAD) systems are growingly influential. This work thus offers a new CAD approach for brain tumour categorisation called RanMerFormer.[11].

Andr´es Anaya-Isaza(2023) et al Our emphasis was on classifying three tumour types: glioma, meningioma, and pituitary. The InceptionResNetV2, InceptionV3, DenseNet121, Xception, ResNet50V2, VGG19, and EfficientNetB7 networks were trained using the Figshare brain tumour dataset. This experiment, which gave an overview of a network's performance, found more than 97% of classifications to be correct. We then concentrated on tumour detection employing the Brain MRI Images for Brain Tumour Detection and the Cancer Genome Atlas's Low-Grade Glioma database.[12].

ABDULLAH A. ASIRI (2024) et al This work presents a new two-module computerised approach meant to boost the speed and accuracy of brain tumour identification. Named the Image Enhancement Technique, the first module normalises images and addresses problems including noise and changing low area contrast using a three-pronged approach combining machine learning and imaging techniques: adaptive Wiener filtration, neural networks, or independent component analysis.[13].

TABLE .1 LITERATURE SUMMARY

Author /Year	Methodology	Result	Limitation	References
Osman Özkaraca(2023)	A custom CNN was built for classifying brain tumors (Glioma, Meningioma, Pituitary, No Tumor) using MRI data, trained with an 80/20 split and 10-fold cross-validation, without transfer learning..	The model achieved 94–97% accuracy, surpassing VGG16, DenseNet, and basic CNNs, thanks to dense layers and a large dataset.	The main limitation is long processing time due to model complexity, and tumor segmentation is not yet implemented.	[14]
Muhammad Attique Khan (2020)	A deep learning pipeline on BraTS data uses contrast enhancement, VGG-	The model achieved up to 98.16% accuracy, with	A key limitation is the reliance on pre-trained models	[15]

	based features, correntropy-ELM selection, and PLS-ELM for tumor classification.	CML-ELM enhancing both performance and efficiency across BraTS datasets.	and multi-stage processing, which may hinder generalization and increase implementation complexity.	
Majdi Alnowami (2022)	A 58-layer DenseNet was trained on 4,314 MRI images (four tumor classes) using 10-fold cross-validation, with preprocessing including augmentation, resizing, skull stripping, and two intensity normalization methods (Z-Score, White-Strip).	The model achieved 96.52% accuracy, 98.5% sensitivity, and 82.1% specificity, with white-strip normalization boosting performance via improved white matter contrast.	White-strip normalization boosts performance but adds processing time and relies on precise white matter segmentation, increasing complexity.	[16]
S. Rinesh(2022)	Hyperspectral images were segmented using firefly-optimized k-means and k-NN clustering, with tumor regions labeled by a multilayer feedforward neural network.	The method achieved 96.47% accuracy, 96.32% sensitivity, and 98.24% specificity, outperforming k-NN, DNN, PSO, LSVM, and DCNN.	The model performs well but could benefit from hybrid deep learning and transfer learning for improved performance and generalization.	[17]
R. Nanmaran (2022)	Brain tumor images from MRI and SPECT were preprocessed using CLAHE and fused with a DCT-based	The fusion-based model achieved 96.8% accuracy with SVM, improving	The method's fusion, feature extraction, and classification steps increased execution time;	[18]

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	technique. Features from the fused images were classified using SVM, KNN, and Decision Tree to distinguish benign and malignant tumors.	classification over individual modalities despite longer processing time	future work could use advanced fusion like Curvelet or Shearlet transforms.	

III. Research Methodology

This work creates a precise multi-class tumour classification tool using an improved brain tumour MRI dataset. To improve image quality and reduce noise, the dataset is subjected to thorough preprocessing including greyscale conversion, adaptive histogram equalisation (CLAHE), and median filtering. Image dimensions, channel characteristics, and class distributions are examined by means of exploratory data analysis (EDA). For texture-based improvement, feature extraction uses Gabor filters; for capturing second-order spatial characteristics, Grey Level Co-occurrence Matrix (GLCM) statistics.[19]. The processed images and handcrafted features are further used to construct two hybrid deep learning models based on ResNet50 and EfficientNetV2B0 architectures, respectively[20]. Both architectures are fine-tuned using ImageNet pre-trained weights and are fused with extracted GLCM features through dense layer concatenation. An 80:20 train-test split strategy and real-time data augmentation are adopted to increase generalization capability. Model performances are evaluated through accuracy metrics, ensuring robust and scalable detection of meningioma, glioma, and pituitary tumors

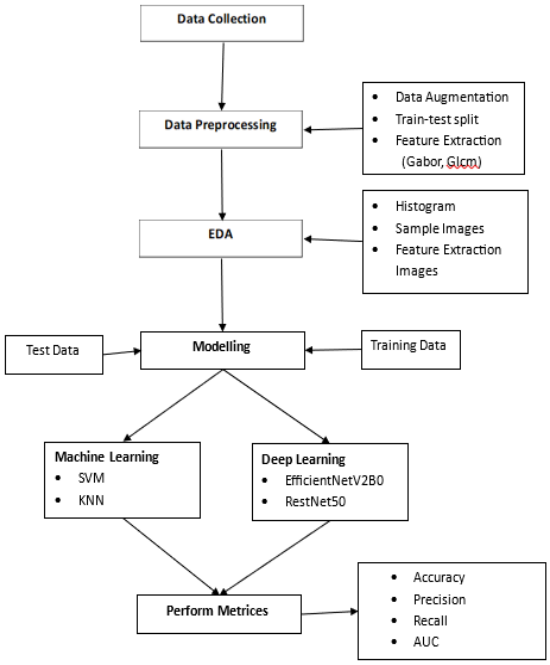

Fig.2 Flow diagram of Methodology

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A. Data collection

The Figshare repository (DOI: 10.6084/m9.figshare.1512427) provided the dataset used in this work. Categorised into three types—meningioma, glioma, and pituitary tumor—the dataset is T1-weighted contrast-enhanced magnetic resonance imaging (MRI) scans of brain tumours. Every image was correctly tagged and gathered under clinical conditions to guarantee great data quality. Organised into several folders according to tumour type, the dataset helps to load and process models during training efficiently. This well-organised dataset provides a solid basis for creating consistent brain tumour classification models

B. Preprocessing

Robust preprocessing is absolutely vital in machine learning to maximise model performance and guarantee consistent outcomes, particularly with huge, unbalanced datasets like those used for brain tumour classification. Data cleaning begins the process; unwanted or superfluous characteristics are eliminated and missing or undefined values are addressed by imputation or deletion. Eliminating any noise or discrepancies that can compromise the performance of the model depends on this stage. The MRI images are then transformed to greyscale, therefore lowering the complexity of the data. Although it speeds up the training process, this simplification enables the model to concentrate on important traits and patterns pertinent to the classification objective. A median blur is also used to lower noise and preserve essential details, especially around the tumour borders, which are crucial for precise tumour identification. All photos are downsized to a uniform size of 224×224 pixels, a standard input dimension for many deep learning models, to guarantee consistency and enhance the model's capacity to generalise. The pixel values are normalised to a range between 0 and 1, which helps in quicker convergence and stabilises the learning process. The training set is finally subjected to data augmentation methods including random rotations, translations, and flips. This enhances the diversity of the data and helps the model to generalise better across differences in the input, therefore preventing overfitting of the model

A two-stage feature extraction pipeline is used post-preprocessing. Gabor filtering is first used on the photos to emphasise localised frequency and orientation information, hence improving edges, ridges, and minor texture changes around tumour borders. The Gray-Level Co-occurrence Matrix (GLCM) is then used to examine the filtered images and so seize spatial correlations among pixel intensities. Six Haralick features—contrast, dissimilarity, homogeneity, angular second moment (ASM), energy, and correlation—are calculated from the GLCM to measure textural patterns and structural anomalies, hence offering a comprehensive set of features for precise tumour classification. This combined approach guarantees a high-quality dataset that enables the creation of strong brain tumour classification models.

C. EDA

Verifying data quality and directing model construction depend much on exploratory data analysis (EDA). Indicating effective normalisation, a histogram of normalised pixel intensities throughout the combined train–test set verifies a smooth, mid–low value distribution. Correct noise reduction and scaling are verified by a 1×3 grid of sample greyscale photos (meningioma,

glioma, pituitary), hence guaranteeing that all classes keep important morphological characteristics. At last, Gabor-filtered examples from the train and test sets side by side emphasise improved edge and texture patterns around tumour areas, hence stressing the extra discriminative information used in later feature extraction. These visualisations reveal the structure of the dataset, hence verifying appropriate preprocessing and preparing the ground for more sophisticated feature engineering. EDA enables the detection of anomalies, outliers, and correlations by means of distribution and important picture features, hence directing model optimisation and performance tuning.

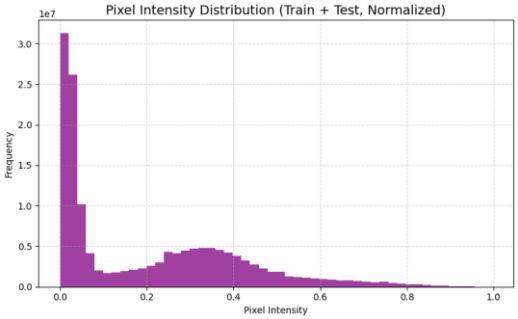

Fig.3 Pixel Intensity Graph

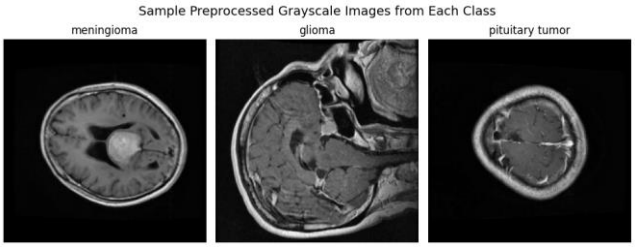

Fig.4 Sample Images from each Classes

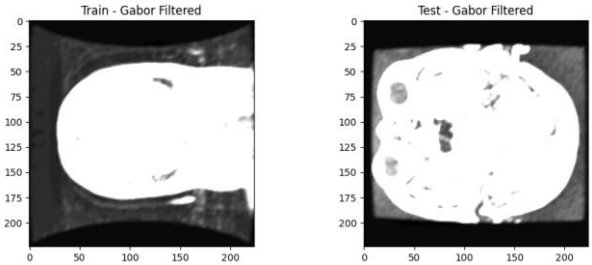

Fig.5 Gabor extracted Features of Images

D. Deep learning models

RestNet50: Classifying brain tumours into three groups, this model is a hybrid deep learning architecture combining ResNet50 (CNN) with handcrafted GLCM (Gray-Level Co-occurrence Matrix) texture characteristics. Using pretrained ResNet50 to extract high-level features from RGB images, the image branch applies GlobalAveragePooling2D, Dense layers with ReLU, Batch Normalisation, and Dropout (0.3) to enhance generalisation and avoid overfitting. Texture characteristics are processed by the GLCM branch using two Dense layers with ReLU; Batch Normalisation and Dropout are also used. For regularising, a last Dense layer with Dropout processes the fused outputs from both branches. Compiled with the Adam optimiser (learning rate of 1e-4) and Sparse Categorical Crossentropy loss, the model classifies using a Softmax activation. The main measuring tool is accuracy.

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Formula

$$Y = \text{Softmax}(W_{out}.\text{GlobalAveragePooling}(\text{ResNet50}(X)) + b_{out})$$

EfficientNetV2: For three-way brain tumour classification, the suggested model is a hybrid deep learning architecture integrating EfficientNetV2B0 (CNN) with handcrafted GLCM texture features. High-level features from RGB inputs are extracted by the image branch using a pre-trained EfficientNetV2B0 (include_top=False), GlobalAveragePooling2D is then applied, and Dense-ReLU layers with Batch Normalisation and Dropout (0.3) are used to enhance generalisation. The GLCM branch, on the other hand, runs the texture feature vector through two Dense-ReLU layers employing Batch Normalisation and Dropout as well. Before a Softmax output layer forecasts the tumour class, the results of both branches are combined and sent into a last Dense-ReLU layer with Dropout. Using Sparse Categorical Crossentropy loss, the Adam optimiser (1e-4) trains the model; accuracy serves as the evaluation criterion.

Formula

$$Y = \text{Softmax}(W_{out} \cdot \text{GlobalAveragePooling}(\text{EfficientNetV2B0}(X)) + b_{out})$$

TABLE. 2 HYPER PARAMETER TABLE OF RESTNET50 AND EFFICIENTNETV2

Parameter	Setting
Image Input	(224×224×3)
GLCM Input	(6,)
Backbone	EfficientNetV2B0 (ImageNet, include_top=False, trainable) RestNet50(ImageNet, include_top=False, trainable)
Pooling	GlobalAveragePooling2D
Dense Units	128 (image), 64 (GLCM), 64 (merged)
Activation	ReLU
Dropout	0.3 (all branches)
Batch Normalization	Yes
Output	3 (Softmax)
Optimizer	Adam (LR=1e-4)
Loss	Sparse Categorical Crossentropy
Metric	Accuracy
Batch Size	32
Epochs	100

E. Machine learning models

SVM: A margin-based classifier that finds the optimal hyperplane to separate classes; with an RBF kernel it captures non-linear patterns, and its regularization parameter C is tuned to balance margin width against misclassification.

Formula:

$$f(x) = w^T x + b$$

KNN: An instance-based method that assigns each sample the majority label of its k closest neighbors in feature space; distance metric and k are selected via cross-validation to balance sensitivity and noise.

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Formula:

$$y = \text{mode}(k - \text{nearest neighbors of } x)$$

IV. Result and Discussion

Three distinct models were applied and run on the dataset to assess the efficacy of several machine learning algorithms for brain tumour classification. After extensive preprocessing—including feature extraction from GLCM and image-based deep learning features—the chosen models—ResNet50-based CNN with GLCM features, Support Vector Machine (SVM), and K-Nearest Neighbours (KNN)—were trained and verified. A strong assessment of the models was obtained by dividing the dataset into training and test sets with an 80:20 ratio. Standard measures like as accuracy, precision, recall, and F1-score were used to assess the models. To enhance classification performance, the ResNet50-based CNN model included handcrafted GLCM features as well as picture features. Trained on the GLCM features, the SVM and KNN models were evaluated for their capacity to precisely categorise brain tumour kinds. Confusion matrix analysis and ROC-AUC score helped to further investigate the performance, which showed the classification ability of the models across several tumour types.

Table 3 Evaluation metrics of ML Models

Model	Training Accuracy	Validation Accuracy	Precision	Recall	AUC	Testing Accuracy
SVM	0.5290	0.5498	0.5313	0.5530	0.7308	0.5530
KNN	0.7173	0.5824	0.6143	0.6166	0.7749	0.6166

This table contrasts the results of two definition models: K-Nearest Neighbours with the support vector machine (SVM) (KNN). SVM achieved lower training accuracy (0.5290) and validation accuracy (0.5498) compared to KNN (0.7173 and 0.5824, respectively). Precision, recall, and testing accuracy also favored KNN, with values of 0.6143, 0.6166, and 0.6166 over SVM's 0.5313, 0.5530, and 0.5530. The Area Under Curve (AUC) metric reflects KNN's better performance (0.7749 vs. 0.7308 for SVM). Overall, KNN demonstrates more reliable classification performance across the metrics, indicating its suitability for the task compared to SVM.

Table 4 Evaluation metrics of DL Models

Model	Training Accuracy	Validation Accuracy	Precision	Recall	AUC	Testing Accuracy
(Proposed) RestNet50	0.9972	0.9250	0.9398	0.9250	0.9948	0.9250
EfficientNetV2	0.9920	0.8157	0.8360	0.8157	0.9504	0.8157

This table compares the performance of two deep learning models: RestNet50 (Proposed) and EfficientNetV2. RestNet50 outperforms EfficientNetV2 across all metrics, achieving significantly higher training accuracy (0.9972 vs. 0.9920), validation accuracy (0.9250 vs. 0.8157), precision (0.9398 vs. 0.8360), recall (0.9250 vs. 0.8157), Area Under Curve (AUC) score (0.9948 vs. 0.9504), and testing accuracy (0.9250 vs. 0.8157). These results highlight

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RestNet50's superior capability for classification tasks, making it the more effective model in this comparison. EfficientNetV2, while robust, demonstrates comparatively lower overall performance.

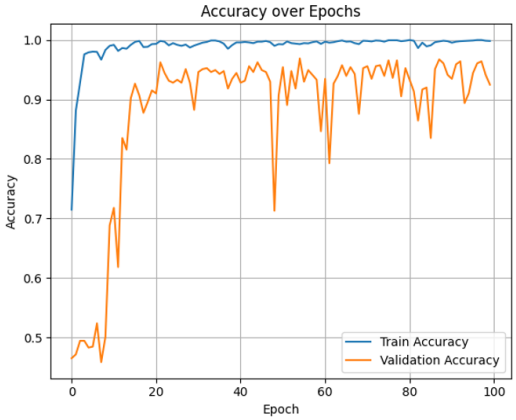

Fig.6 Proposed model Accuracy Curve

RestNet50 achieves exceptional performance, with near-perfect training accuracy (0.9972), high validation and testing accuracy (0.9250), and excellent precision, recall, and AUC scores, showcasing its superior capability for classification tasks

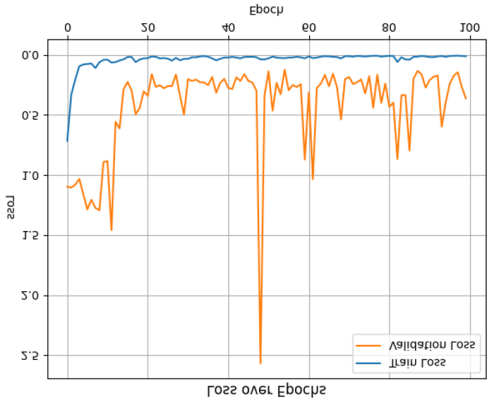

Fig.7 Proposed model Loss Curve

The graph represents the training and validation loss trends for RestNet50 across epochs. Training loss decreases steadily, while validation loss stabilizes, indicating effective model generalization and minimal overfitting

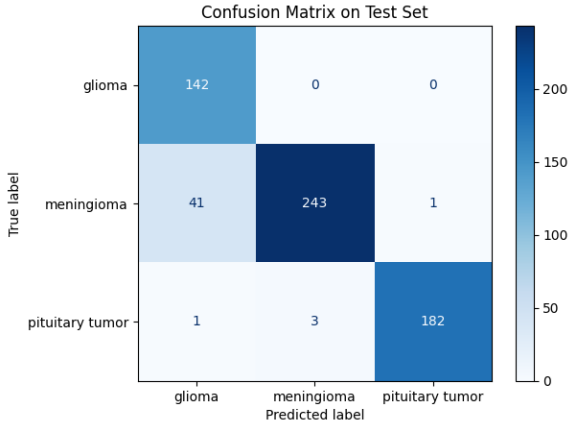

Fig.8 Proposed model confusion Matrix

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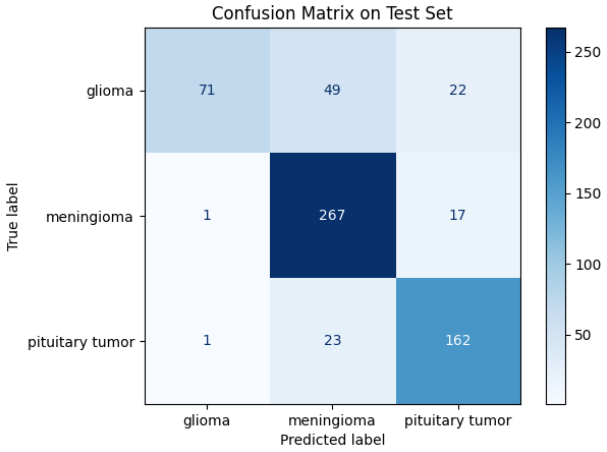

Fig .9 EfficientNetV2 Confusion Matrix

A confusion matrix assessing a model's classification of three tumour types—glioma, meningioma, and pituitary—the graph While off-diagonal values draw attention to errors, the diagonal indicates accurate forecasts and helps to evaluate model accuracy. Indicating good generalisation, the ResNet50-based model achieved a training accuracy of 99.72% or a validation accuracy of 92.50%.

V. Conclusion

Outstanding results in the job of brain tumour classification have been shown by the suggested model combining ResNet50 with Gray-Level Co-occurrence Matrix (GLCM) characteristics. The model stands out in properly separating between various brain tumour kinds with a training accuracy of 99.72% and a validation accuracy of 92.50%. The model's capacity to detect minute patterns that could otherwise be missed is further improved by include GLCM features, which gather textural data from the photos. The ResNet50-based model stands out in comparison to other deep learning models, such as EfficientNetV2B0, which attained a validation accuracy of 81.57%, because of its better performance.

Apart from the deep learning models, conventional machine learning methods such Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) were also evaluated for contrast. Although these models performed rather well—SVM attaining a validation accuracy of about 80% and KNN exhibiting comparable performance—they were not as good as the ResNet50. Through convolutional layers, the deep learning method—especially with the ResNet50 architecture—efficiently uses sophisticated visual features, therefore enabling improved generalisation and classification accuracy.

The results highlight the benefits of deep learning over conventional machine learning models in medical picture classification tasks, particularly when complicated, high-dimensional data is involved. The model can provide remarkable accuracy and durability by integrating handmade GLCM features with the strength of ResNet50, a state-of-the-art convolutional neural network. This method emphasises the possibility of enhancing the effectiveness of medical picture classification by combining deep learning with feature extraction techniques, especially for uses such as brain tumour diagnosis.

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