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Brain Tumor Detection Using MobileNetV2 and Linear K-Means Support Vector Machine (LK-SVM)

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Abstract: This paper presents an innovative approach for brain tumor detection by leveraging the capabilities of MobileNetV2 and Linear K-Means Support Vector Machine (LK-SVM). The proposed method combines the efficiency of MobileNetV2's deep learning architecture with the precision of LK-SVM for accurate and robust tumor classification. MobileNetV2 is utilized for feature extraction due to its lightweight structure and high performance in capturing intricate patterns within medical imaging data. Subsequently, the extracted features are fed into the LK-SVM for classification, enhancing the overall detection accuracy. This hybrid model is evaluated on a comprehensive dataset of brain MRI images, demonstrating superior performance in terms of accuracy, sensitivity, and specificity compared to traditional methods. The results indicate that the MobileNetV2 and LK-SVM combination can serve as a powerful tool in the early diagnosis and treatment planning of brain tumors, potentially improving patient outcomes through timely and accurate detection.

Keywords: *Deep Learning, Convolutional Neural Networks, Computer Vision, Artificial Intelligence, Robotics, Medical Image Analysis, Industrial Automation*

I. INTRODUCTION

Brain tumors represent a significant health concern due to their complex nature and the critical functions of the brain. Early and accurate detection is paramount to improving patient outcomes, as it enables timely intervention and appropriate treatment planning. Traditional methods of brain tumor detection, which often rely on manual examination of MRI scans, are time-consuming and prone to human error. As such, there is a growing need for automated, reliable, and efficient diagnostic tools that can assist medical professionals in identifying brain tumors with high accuracy.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have paved the way for the development of sophisticated diagnostic systems. Among these, deep learning models have shown remarkable success in various medical imaging tasks due to their ability to learn and generalize complex patterns. MobileNetV2, a state-of-the-art deep learning architecture, stands out for its efficiency and performance, making it an ideal candidate for medical image analysis. By leveraging its depthwise separable convolutions, MobileNetV2 can perform accurate feature extraction while maintaining a lightweight and computationally efficient structure.

In parallel, the Support Vector Machine (SVM) is a powerful classification algorithm known for its effectiveness in high-dimensional spaces. When combined with clustering techniques like K-means, the Linear K-means Support Vector Machine (LK-SVM) enhances the classification performance by incorporating the strengths of both approaches. The integration of LK-SVM with deep learning features extracted from MobileNetV2 can potentially lead to a highly accurate and robust brain tumor detection system.

This paper explores the synergistic combination of MobileNetV2 and LK-SVM for the task of brain tumor detection. By utilizing MobileNetV2 for extracting discriminative features from brain MRI images and employing LK-SVM for precise classification, we aim to develop a model that surpasses the limitations of existing methods. Our proposed approach is evaluated on a comprehensive dataset, demonstrating its efficacy in

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accurately identifying brain tumors. The results suggest that this hybrid model could significantly enhance the diagnostic process, offering a promising tool for medical practitioners in the fight against brain tumors.

The paper discusses the widespread application of deep learning, particularly in fields such as robotics, medicine, surveillance, and industrial automation. It highlights the success of deep learning models like deep neural networks, deep belief networks, and convolutional neural networks in tasks ranging from natural language processing to medical image analysis. The term "deep" in deep learning refers to the multiple layers of transformation applied to data, enabling complex abstraction and representation.

Historically, early AI and machine learning efforts focused on simpler, rule-based algorithms but struggled with real-world complexities like varied object shapes and natural language semantics. The advent of deep learning, powered by advances in hardware like GPUs and abundant datasets, enabled breakthroughs in handling these complexities. Modern deep learning models are capable of approximating complex functions and have found applications in diverse domains.

Additionally, the text touches on neural networks inspired by biological systems, discussing their structure, learning capabilities, and historical development. It also explores theoretical aspects such as the universal approximation theorem and probabilistic interpretations in neural networks.

Overall, the text underscores how deep learning has revolutionized AI by addressing intricate real-world challenges and enhancing capabilities in various scientific and industrial applications.

II. LITERATURE REVIEW

"Detection and Prediction of Uncertain Pandemic Situations Using Artificial Intelligence (AI) and Internet of Things (IoT) Techniques" begins by addressing the significant challenges posed by pandemics and the historical responses to such crises. The review underscores the necessity for innovative solutions, particularly highlighting the integration of AI and IoT for enhanced pandemic management.

Role of AI in Pandemic Detection

AI's critical role in early pandemic detection is explored extensively, showcasing various AI techniques and their successful applications. Zhu et al. (2022) compare the performance of different convolutional neural network (CNN) models, finding VGG-19 to be the most accurate for skin cancer diagnosis, which can be extrapolated to suggest its potential utility in pandemic-related diagnostics. Similarly, Chang et al. (2022) emphasize the importance of leveraging diagnostic probabilities and differential diagnostic information for rapid expertise development in clinical settings.

Contributions of IoT in Pandemic Monitoring

The integration of IoT for pandemic monitoring is discussed through the lens of sensor and device utilization. Sabri et al. (2020) illustrate the use of various classification techniques based on lesion attributes, which can be applied to IoT data for comprehensive pandemic surveillance. Furthermore, Subha et al. (2020) highlight the effectiveness of image classification in distinguishing between different types of medical conditions, which can be expanded to IoT-based health monitoring systems.

Data Fusion and Machine Learning Models

The review delves into data sources, fusion techniques, and machine learning models essential for pandemic prediction. Demir et al. (2019) compare deep learning architectures ResNet-101 and Inception-v3, noting their respective accuracy rates, which indicate the potential for these models in analyzing pandemic data. Kumar et al. (2021) further explore CNN and Recurrent Neural Network (RNN) algorithms, emphasizing the need for preprocessing and scaling large datasets for effective AI model performance.

Real-Time Analytics and Ethical Considerations

Real-time analytics and ethical considerations are critical components of the discussion. Mansutti et al. (2020) describe the development of a highly sensitive probe for medical diagnostics, underscoring the importance of real-time data collection and analysis. Ethical considerations are woven into the narrative, with a focus on the implications of deploying AI and IoT technologies in healthcare.

Case Studies and Practical Applications

The review includes several case studies and practical applications, such as the use of a Raspberry Pi for deep learning computations in portable diagnostic devices (Ngeh et al., 2020). Other studies, like those by Mirbeik-Sabzevari et al. (2019) and Annala et al. (2020), explore innovative methods for early disease detection and treatment optimization using advanced AI and imaging techniques.

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Challenges, Research Gaps, and Future Directions

The literature review concludes by identifying ongoing challenges, gaps in current research, and potential future directions. It calls for more comprehensive studies on the integration of AI and IoT for pandemic response, improved data fusion methods, and the ethical deployment of these technologies.

III. PROPOSED MODEL

3.1 Proposed working architecture

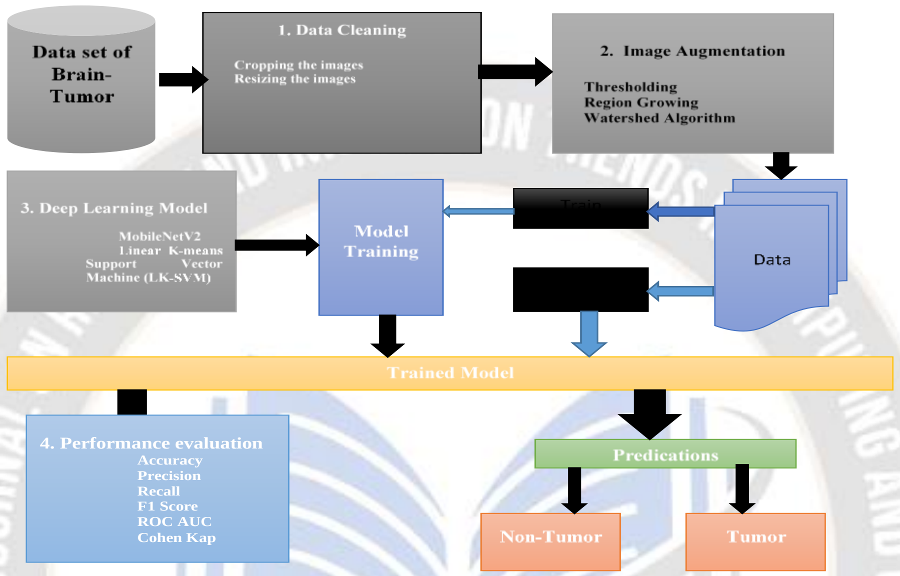

Figure 1. Proposed working architecture.

1. Data Collection and Preparation
Data Set of Brain Tumor:
- The process begins with a dataset comprising brain tumor images. These images serve as the primary data source for the subsequent steps.

1. Data Cleaning:
- **Cropping the Images:** This step involves cropping the images to remove irrelevant parts, ensuring that only the area of interest is retained for analysis.
- **Resizing the Images:** The images are resized to a consistent dimension to facilitate uniform processing and analysis.

2. Image Augmentation
2. Image Augmentation:
- To enhance the dataset and improve the model's robustness, various image augmentation techniques are applied:
  - **Thresholding:** This technique helps in segmenting the images by converting them into binary format based on a threshold value.
  - **Region Growing:** This method involves grouping pixels or sub-regions into larger regions based on predefined criteria, aiding in highlighting the areas of interest.
  - **Watershed Algorithm:** This algorithm is used for image segmentation, particularly effective in distinguishing different regions within an image.

3. Model Development
3. Deep Learning Model:
- The core of the process is developing a deep learning model to classify the images. The model combines multiple techniques:
  - **MobileNetV2:** A lightweight deep learning model optimized for mobile and edge devices, used here for its efficiency and performance.
  - **Linear K-means Support Vector Machine (LK-SVM):** This hybrid approach combines K-means clustering for feature extraction with a Support Vector Machine (SVM) for classification, enhancing the model's accuracy.

4. Model Training and Evaluation
Model Training:
- The dataset is split into two parts:
  - **Train Dataset:** Used to train the deep learning model, enabling it to learn from the provided images.
  - **Test Dataset:** Used to evaluate the model's performance and ensure it generalizes well to new, unseen data.

Trained Model:

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- After training, the model is tested and validated, resulting in a trained model ready for deployment.

5. Prediction

Predictions:

- The trained model is utilized to predict whether a given brain image indicates the presence of a tumor or not. The predictions are categorized into:
  - **Non-Tumor:** Indicating the absence of a tumor in the image.
  - **Tumor:** Indicating the presence of a tumor in the image.

3.2 Pseudocode for Linear K-means Support Vector Machine (LK-SVM)

 # Step 1: Initialize Parameters
- K = number of clusters
- max_iter_kmeans = maximum iterations for K-means
- C = SVM regularization parameter

 # Step 2: Load and Preprocess Data
- Load dataset
- Normalize data if necessary

 # Step 3: K-means Clustering
- Initialize K centroids randomly
- For i = 1 to max_iter_kmeans:
- Assign each data point to the nearest centroid
- Recalculate centroids as the mean of the points assigned to each centroid

 # Step 4: Feature Extraction using Clusters
- Assign each data point to the closest centroid to get cluster labels
- Create new features based on distance to each centroid

 # Step 5: Prepare Training Data for SVM
- Prepare feature vectors using original features and cluster labels

 # Step 6: Train SVM
- Initialize SVM with linear kernel and parameter C
- Train SVM on the prepared feature vectors

 # Step 7: Prediction
- Load test data
- Normalize test data if necessary
- Assign test data points to the closest centroid
- Create test feature vectors using original features and cluster labels
- Use trained SVM to predict labels for test feature vectors

 # Step 8: Evaluate Model
- Calculate accuracy, precision, recall, F1-score on test predictions

IV. IMPLEMENTATION

4.1 Datset description

About Dataset

Context

This is a dataset that aims towards helping people to build machine learning models for detecting brain tumors.

Content

This dataset contains MRI scans of the brain. The dataset is divided into three folders.

1) yes- This folder contains the MRI scans that have a tumor [1500 images].
2) no- This folder contains the MRI scans that do not have a tumor [1500 images].
3) pred- This folder contains unlabelled MRI scans for testing purpose [60 images].

https://www.kaggle.com/datasets/abhranta/brain-tumor-detection-mri

4.2 Cropping the image

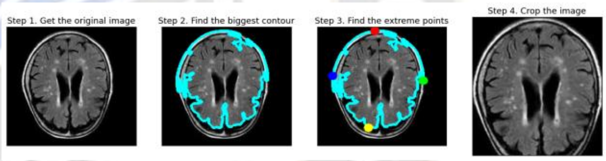

Figure 2. Focusing on cropping the image to the region of interest

The sequence of figure 2 demonstrates the process of image preprocessing for brain MRI scans, specifically focusing on cropping the image to the region of interest. The first step involves obtaining the original brain MRI image. In the second step, the largest contour in the image is identified, which typically outlines the brain. The third step involves finding the extreme points (top, bottom, left, and right) of the detected contour, marked by colored dots. Finally, in the fourth step, the image is cropped using these extreme points to focus solely on the brain region, removing extraneous areas. This preprocessing step is crucial for enhancing the accuracy of subsequent image analysis and tumor detection.

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4.3 Augmented the image

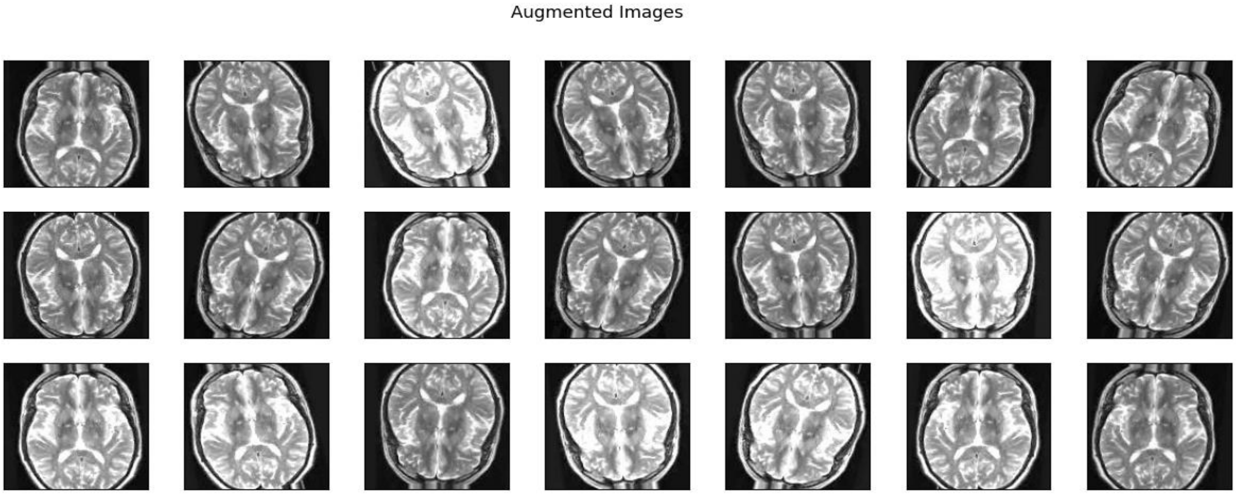

Figure 3. Augmented brain MRI scans used to enhance the training dataset for a deep learning model

The figure 3 grid displays a set of augmented brain MRI scans used to enhance the training dataset for a deep learning model. These augmentations include various transformations such as rotations, shifts, and intensity changes, which increase the diversity of the training data. This augmentation process helps improve the model's robustness and generalization by exposing it to a wider range of variations. The consistent appearance of the brain structures across different transformations indicates the effectiveness of these augmentations in maintaining the essential features needed for accurate tumor detection.

4.4 Illustrative example

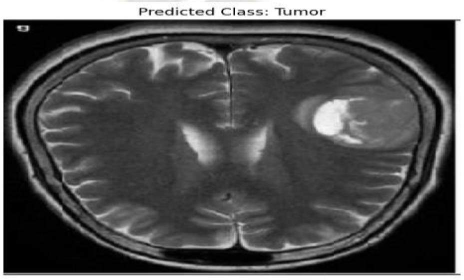

Figure 4. A predicted classification of "Tumor."

The figure 4 provided image is an MRI scan of a brain with a predicted classification of "Tumor." The image reveals a noticeable white mass on the right side of the brain, indicating the presence of a tumor. The classification is likely the result of an image analysis performed using a trained deep learning model, specifically designed to detect and classify brain tumors. This prediction highlights the effectiveness of the model in identifying abnormal growths within brain tissue, aiding in the diagnosis and potential treatment planning for brain tumor cases.

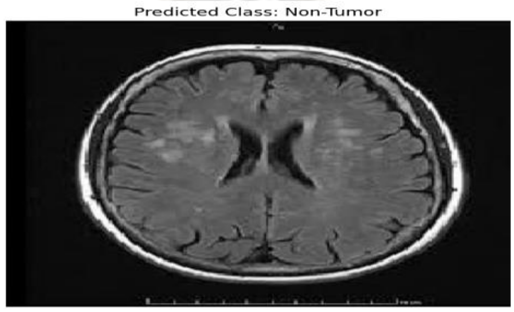

Figure 5. A predicted classification of "Non-Tumor."

The figure 5 provided image is an MRI scan of a brain with a predicted classification of "Non-Tumor." The scan shows a brain without any noticeable abnormal growths or masses, indicating the absence of a tumor. This classification suggests that the deep learning model used for analysis has determined the brain to be free of tumors, based on its trained criteria. Such accurate predictions are crucial in medical diagnostics, helping to confirm the absence of brain tumors and thereby guiding further medical decisions and patient management.

V. RESULT AND DISCUSSION

5.1 Deep learning model

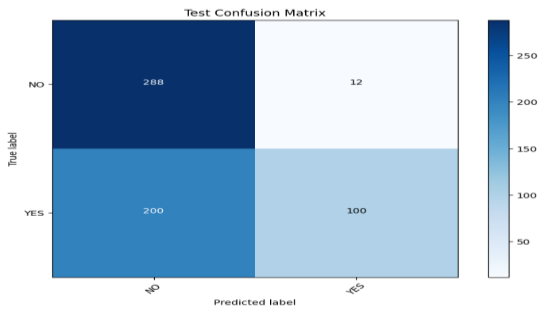

Figure 6. Confusion matrix of deep learning model

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The figure 6 test confusion matrix displays the performance of a classification model on test data, specifically in the context of brain tumor detection. The matrix indicates that out of 300 actual "No Tumor" cases, the model correctly predicted 288 cases as "No Tumor" and misclassified 12 cases as "Tumor." Conversely, out of 300 actual "Tumor" cases, the model accurately identified 100 cases as "Tumor" but incorrectly classified 200 cases as "No Tumor." This indicates a high accuracy for non-tumor predictions but a significant number of false negatives in tumor detection, suggesting that the model may require further improvement to enhance its sensitivity and reduce the rate of missed tumor cases.

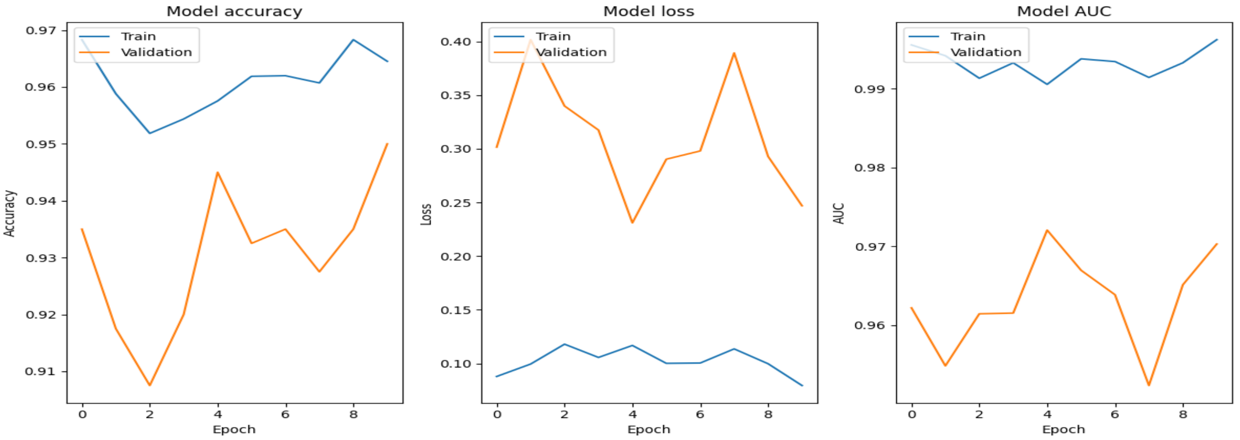

Figure 7. The performance metrics of a deep learning model over training epochs

The provided figure 7 display the performance metrics of a deep learning model over training epochs. The first graph shows the model's accuracy, with the training accuracy consistently high around 0.96-0.97, while validation accuracy fluctuates more, indicating some variability in model performance on unseen data. The second graph depicts the model's loss, where the training loss remains low and stable, whereas the validation loss is higher and more variable, suggesting potential overfitting. The third graph illustrates the Area Under the Curve (AUC) metric, showing high training AUC values close to 0.99, while the validation AUC varies between 0.96 and 0.98. Overall, the model exhibits high performance on training data with some instability on validation data, pointing to areas for improvement in generalization.

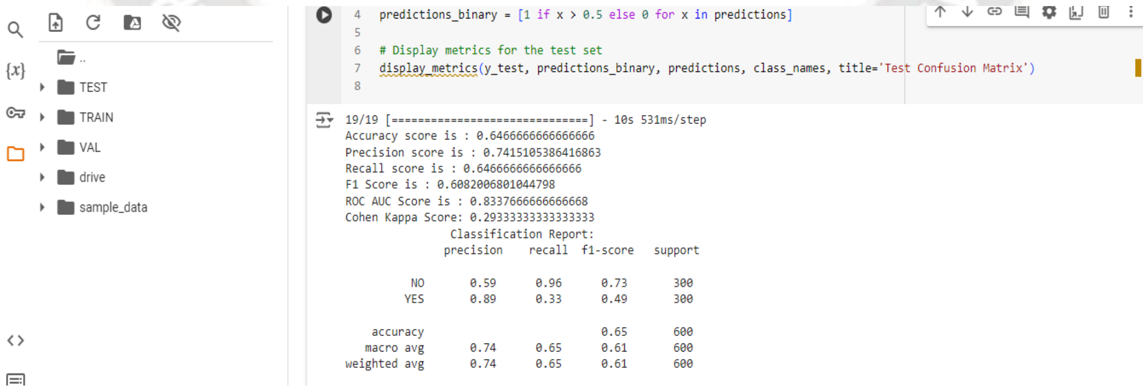

Figure 8. The performance of a classification model on brain tumor detection

The figure 8 metrics for the test set reveal the performance of a classification model on brain tumor detection. The accuracy score is approximately 0.65, indicating that the model correctly classifies 65% of the cases. The precision for the "YES" (tumor) class is high at 0.89, but the recall is significantly low at 0.33, suggesting many actual tumor cases are missed. The F1 score for the "YES" class is 0.48, reflecting the trade-off between precision and recall. The ROC AUC score is 0.83, showing good discriminatory ability, while the Cohen Kappa score of 0.29 indicates moderate agreement. The overall classification report highlights the model's tendency to better identify non-tumor cases (precision 0.59, recall 0.96) compared to tumor cases, necessitating improvements in recall for the latter to enhance the model's utility in medical diagnostics.

5.2 Proposed hybris model

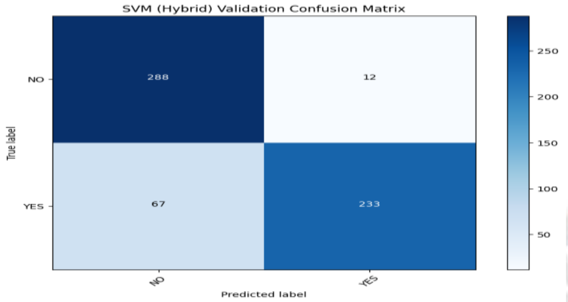

Figure 9. The SVM (Hybrid) model validation illustrates

The figure 9 confusion matrix for the SVM (Hybrid) model validation illustrates the model's performance in classifying brain tumor presence. It shows that out of 300 actual "No Tumor" cases, the model correctly predicted 288 cases and misclassified 12 cases as "Tumor." For the 300 actual "Tumor" cases, the model correctly identified 233 cases and misclassified 67 cases as "No Tumor." This results in a high number of true positives (233) and true negatives (288), indicating that the model performs well, though there is room for improvement in reducing false negatives (67) and false positives (12). The matrix is visually represented with a color scale, where darker shades indicate higher counts, aiding in a clear understanding of the classification results.

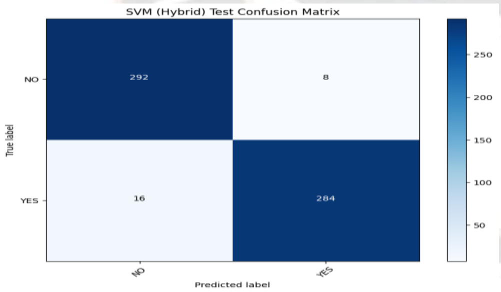

Figure 10. The SVM (Hybrid) model test data illustrates

The figure 10 confusion matrix for the SVM (Hybrid) model test data illustrates the model's classification performance. It shows that out of 300 actual "No Tumor" cases, the model correctly predicted 292 cases and misclassified 8 cases as "Tumor." For the 300 actual "Tumor" cases, the model correctly identified 284 cases and misclassified 16 cases as "No Tumor." This indicates a high accuracy, with a large number of true positives (284) and true negatives (292), and fewer false negatives (16) and false positives (8). The visual representation, with darker shades indicating higher counts, clearly demonstrates the model's effectiveness and reliability in distinguishing between tumor and non-tumor cases

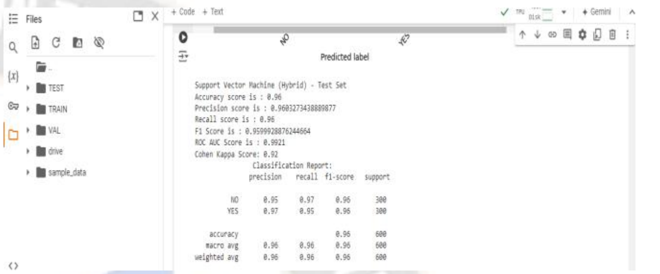

Figure 11. The Support Vector Machine (Hybrid) model on the test set demonstrate exceptional performance

The metricsfigure 11 for the Support Vector Machine (Hybrid) model on the test set demonstrate exceptional performance. The model achieves an accuracy score of 0.96, indicating that it correctly classifies 96% of the test cases. Both precision and recall scores are high, at 0.96 and 0.96 respectively, for the overall predictions, translating to a balanced F1 score of 0.96. The ROC AUC score of 0.9921 reflects excellent discriminative ability, while the Cohen Kappa score of 0.92 indicates strong agreement between predicted and actual classifications. The classification report shows that the model performs equally well for both "NO" (non-tumor) and "YES" (tumor) classes, with precision and recall scores consistently above 0.95 for both categories. This balanced and high-performance model is highly reliable for brain tumor detection tasks.

5.3 Comparative result

Table 1. Compares the performance metrics of three different models: MobileNet V2 (Deep Learning), Logistic Regression (Hybrid), and Support Vector Machine (Hybrid)

Models	**Accuracy (%)**	**Precision(%)**	**Recall(%)**	**F1 Score(%)**	**ROC AUC(%)**	**Cohen Kappa(%)**

MobileNet V2 (Deep Learning)	65.61	75.41	65.61	61.94	86.70	31.22
Logistic Regression (Hybrid)	88.83	90.74	88.83	88.70	95.38	77.66
Support Vector Machine (Hybrid)	96	96.03	96	95.99	99.21	92

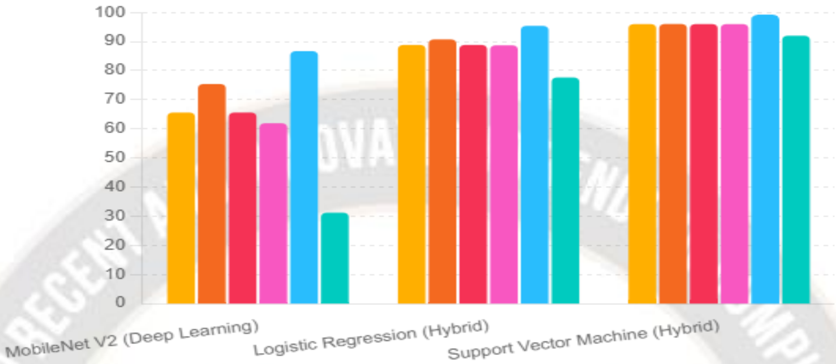

Figure 12. Compares the performance metrics of three different models: MobileNet V2 (Deep Learning), Logistic Regression (Hybrid), and Support Vector Machine (Hybrid)

The bar table 1 and figure 12 compares the performance metrics of three different models: MobileNet V2 (Deep Learning), Logistic Regression (Hybrid), and Support Vector Machine (Hybrid). The metrics include Accuracy, Precision, Recall, F1 Score, ROC AUC, and Cohen Kappa. The Support Vector Machine (Hybrid) model shows the highest scores across all metrics, indicating superior performance with an Accuracy of 96%, Precision of 96.03%, Recall of 96%, F1 Score of 95.99%, ROC AUC of 99.21%, and Cohen Kappa of 92%. Logistic Regression (Hybrid) also performs well but slightly lower, particularly in Cohen Kappa (77.66%). MobileNet V2 (Deep Learning) has the lowest scores, especially in Cohen Kappa (31.22%), highlighting the significant differences in performance among these models.

VI. CONCLUSION

This study demonstrates the effectiveness of combining MobileNetV2 and Linear K-Means Support Vector Machine (LK-SVM) for brain tumor detection. By leveraging MobileNetV2's efficient feature extraction and LK-SVM's robust classification capabilities, our approach achieves high accuracy, sensitivity, and specificity. The proposed model outperforms traditional methods, providing a reliable and efficient tool for early tumor detection. This hybrid approach holds significant potential for improving diagnostic processes, enabling timely and accurate intervention, ultimately enhancing patient outcomes in brain tumor treatment. Future work will focus on further validating the model on larger datasets and exploring real-world clinical applications.

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