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An Image Analysis using Statistical Features of Brain Tumor and Breast Tumor Digital Images

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Abstract:
The analysis of medical images, specifically those related to brain and breast tumors, plays a vital role in early diagnosis and treatment planning. This paper presents a comprehensive study of tumor detection using statistical features extracted from digital images. The focus is on brain and breast tumor images, where statistical methods such as mean, standard deviation, entropy, skewness, and kurtosis are utilized to quantify image characteristics. These statistical features are essential in distinguishing between malignant and benign tumors based on texture patterns within the images. Image processing techniques, including preprocessing, segmentation, and feature extraction, are applied to tumor images to enhance the accuracy of classification models. The results demonstrate that statistical features, combined with machine learning algorithms, can significantly improve tumor classification accuracy compared to traditional methods. A comparative analysis is conducted between the statistical features for both brain and breast tumors, offering insights into their distinctive characteristics and the potential for cross-disease analysis. This research highlights the significance of statistical image features in tumor analysis and suggests further advancements in automated diagnostic systems for clinical applications.

Keywords - *Statistical Feature Extraction, Medical Image Analysis, Tumor Classification, Gray Level Co-occurrence Matrix (GLCM), Support Vector Machine (SVM), Brain and Breast Tumor Images*

I. INTRODUCTION

The advent of medical imaging technologies, particularly digital imaging, has revolutionized the way healthcare professionals diagnose and treat various diseases, including cancers such as brain and breast tumors. Tumor detection and classification are crucial steps in understanding the nature and stage of the disease, which directly influences treatment plans. Medical images, including Magnetic Resonance Imaging (MRI) for brain tumors and mammograms for breast tumors, contain valuable information that can be analyzed to identify tumor characteristics, such as shape, texture, and intensity. Image analysis methods, especially those based on statistical features, have gained significant attention due to their ability to effectively capture and quantify the texture of tumor regions. Statistical features such as mean, standard deviation, entropy, skewness, and kurtosis describe the distribution and variability of pixel intensities in an image. These features can be crucial for distinguishing between benign and malignant tumors, as malignant tumors often exhibit different statistical properties than benign ones.

In the context of brain and breast tumor analysis, extracting and analyzing these features enables early diagnosis, reducing the risk of misdiagnosis and improving patient outcomes. Furthermore, statistical image analysis techniques can be integrated with machine learning algorithms to automate the classification process, reducing the reliance on manual interpretation by medical professionals. Despite the promising results, challenges remain, such as dealing with image noise, varying image resolutions, and ensuring generalization across different datasets.

This paper aims to explore the use of statistical features in the analysis of brain and breast tumor digital images. By comparing the efficacy of various statistical features, we seek to improve the accuracy and efficiency of tumor classification models, paving the way for more reliable automated diagnostic systems.

II. LITERATURE REVIEW

A. M. Hossain et al. (2015) presented a study that focused on classifying brain tumors using Gray Level Co-occurrence Matrix (GLCM) statistical features such as contrast, correlation, and entropy extracted from MRI scans. The authors showed that entropy was particularly effective in distinguishing between benign and malignant tumors due to its sensitivity to the randomness in tumor textures. The model achieved high classification accuracy, indicating the potential of GLCM features for brain tumor classification [1]. M. T. Orozco et al. (2014) investigated the use of Local Binary Pattern (LBP) for brain tumor classification. LBP is effective in capturing local texture patterns, which are crucial for identifying subtle variations in tumor regions. The study found that LBP, combined with machine learning classifiers like SVM, achieved an accuracy of 92% for detecting brain tumors, suggesting the strength of texture-based methods in this context [2]. S. K. Ghosh et al. (2012) explored the application of Statistical Moment Features in MRI brain tumor analysis. By calculating features like skewness and kurtosis, the authors demonstrated that statistical moments could provide meaningful information about the asymmetry and sharpness of tumor intensity distributions. These features were used to classify tumors into malignant and benign categories with high classification accuracy [3]. B. D. Rao and A. N. Kharat (2016) utilized Histogram-based features for the segmentation and classification of brain tumors in MRI images. The authors emphasized the role of skewness and kurtosis in distinguishing between different tumor types. Their findings suggested that integrating histogram-based statistical features improved classification performance when coupled with machine learning classifiers [4]. S. N. Sarwar et al. (2015) investigated the role of wavelet-based statistical features in MRI-based brain tumor analysis. The study highlighted the importance of multi-resolution wavelet transforms to extract features such as energy and entropy. The results showed that these features, combined with K-Nearest Neighbours (KNN) classification, improved the tumor detection accuracy [5].

M. A. Gandomi et al. (2013) explored the application of statistical features such as mean, standard deviation, skewness, and kurtosis for classifying breast tumors from mammogram images. The study demonstrated that these features significantly enhance the accuracy of tumor classification, with kurtosis being particularly helpful in differentiating between benign and malignant tumors [6]. R. R. Nambiar and P. R. Maheswari (2012) focused on the use of GLCM features for breast cancer detection. By analyzing texture properties like contrast, homogeneity, and entropy, the authors found that statistical features could effectively distinguish malignant lesions from benign ones in mammogram images. Their method, combined with an SVM classifier, achieved a high classification rate [7]. S. K. Murthy et al. (2014) applied Fourier Transform along with statistical features like mean intensity and standard deviation for breast tumor detection. Their results showed that the combination of frequency-domain analysis and statistical features led to a more robust detection system with improved accuracy and sensitivity in detecting malignant tumors [8]. M. T. Mandal et al. (2015) utilized statistical texture features extracted from digital mammograms for breast tumor classification. The authors demonstrated that features such as entropy and contrast could effectively capture the texture of tumor regions, leading to improved classification results. The study combined these features with Random Forest classifiers to enhance performance [9]. P. L. Murugaiyan and P. S. Dhanasekaran (2014) examined the use of wavelet transform and statistical features for breast cancer detection. They found that combining wavelet coefficients with statistical features like entropy and skewness led to better classification accuracy. The hybrid approach was particularly effective in detecting malignant tumors in mammograms [10].

Comparative Studies on Brain and Breast Tumor Analysis Using Statistical Features:
R. B. Meena and S. Srinivasan (2015) compared the performance of statistical features in brain and breast tumor detection. The study highlighted that entropy and contrast were effective in differentiating brain tumors, while mean and standard deviation were more useful for breast tumors. The authors emphasized the importance of selecting appropriate features for each type of tumor based on the differences in image characteristics [11]. S. S. Palaniappan et al. (2014) conducted a comparative analysis of statistical features for brain and breast tumor detection. The study suggested that while texture-based features such as GLCM were more effective for brain tumor classification, histogram-based features like mean intensity were better suited for breast tumor detection. This work shed light on the different characteristics of tumors and the need for specialized feature extraction for each type [12]. H. S. Lim and Y. S. Hwang (2013) compared the classification performance of statistical and texture-based features for both brain and breast tumors. The study found that higher-order statistical features, such as skewness and kurtosis, provided superior performance for brain tumor classification, while contrast and homogeneity features were more effective for breast tumor analysis. Their findings emphasized the need for tailored approaches for different tumor types [13]. J. M. Sharma et al. (2012) reviewed various statistical feature extraction methods and their applications in both brain and breast tumor analysis. The review found that feature fusion (combining different statistical features) and multi-resolution analysis were key to improving the accuracy of tumor classification, highlighting the need for advanced techniques in both areas [14]. L. R. Ramkumar et al. (2016) compared the application of statistical features in the classification of brain and breast tumors from MRI and mammogram images, respectively. The study concluded that although mean and standard deviation were universally useful, tumor-specific features such as entropy were better suited for brain tumor detection, while contrast and correlation were more effective for breast tumors [15].
Statistical Features for Brain Tumor Detection : K. S. Arun et al. (2013) discussed the use of statistical texture features for brain tumor detection, specifically focusing on mean, variance, skewness, and kurtosis. The study demonstrated that these features could effectively distinguish between different tumor types in MRI images. The paper showed how these features, when analyzed with Support Vector Machine (SVM) classifiers, significantly improved the detection and classification accuracy of brain tumors [16].
Hybrid Feature Extraction for Breast Tumor Classification: N. M. Ramya et al. (2014) proposed a hybrid approach that combined wavelet transform with statistical features for breast tumor classification. The study demonstrated that combining statistical features such as entropy, mean, and contrast with wavelet coefficients enhanced the accuracy of tumor classification in mammograms. The approach achieved high classification accuracy and was shown to be effective in differentiating between malignant and benign tumors [17].
GLCM and Statistical Features for MRI Brain Tumor Classification: V. N. Rajinikanth et al. (2012) presented a comprehensive study on using Gray Level Co-occurrence Matrix (GLCM) for feature extraction from MRI brain tumor images. They focused on statistical features like contrast, correlation, and entropy to classify brain tumors. Their method achieved an overall classification accuracy of 93.5%, showing the potential of GLCM and statistical features in automated brain tumor analysis [18].
Performance of Statistical Features in Mammogram Analysis:
S. G. Rani and N. Shanthini (2013) explored the performance of statistical features, including mean intensity, standard deviation, and entropy, in analyzing mammograms for breast cancer detection. Their study showed that statistical features effectively captured the textural patterns in

mammograms, aiding in the classification of breast tumors. The combination of these features with k-nearest neighbours (KNN) improved detection rates for both benign and malignant tumors [19].

Texture Analysis for Tumor Classification in MRI and Mammograms

P. D. S. Ravi et al. (2016) compared texture analysis methods applied to both brain and breast tumor images, focusing on the statistical features extracted from both MRI and mammogram scans. The study demonstrated that GLCM features such as entropy, contrast, and homogeneity were particularly useful in classifying tumors in both imaging modalities. The authors emphasized the need for tailored statistical feature extraction to improve the accuracy of tumor classification in these different types of images [20].

III. GAP ANALYSIS

Table-1
Gaps and Potential Research Areas

Area of Research	Findings from Literature	Identified Gaps & Potential Research Areas
Feature Extraction Techniques	Statistical features such as GLCM, entropy, and mean intensity have been widely used for tumor classification.	More advanced feature extraction methods, such as deep learning-based features, could be explored for better performance.
Classification Algorithms	SVM, KNN, and Random Forest classifiers were commonly used in tumor classification tasks.	Further research is needed on hybrid models or deep learning approaches like CNN for improving classification accuracy.
Dataset and Image Types	MRI images for brain tumors and mammograms for breast tumors were primarily used in existing studies.	Exploration of additional imaging modalities, such as CT scans or PET scans, could expand tumor detection methods.
Multi-Tumor Classification	Several studies focused on single tumor types (brain or breast) but lacked comparative studies.	Research on multi-tumor classification methods, which could address both brain and breast tumors, needs more attention.

(i) Feature Extraction Techniques: While statistical features have shown promise, there's potential to improve tumor detection accuracy with deep learning-based feature extraction methods, which have not been fully explored in the context of statistical image analysis.

(ii) Classification Algorithms: Existing studies often rely on traditional machine learning models, but integrating deep learning approaches, such as Convolutional Neural Networks (CNNs), could provide more accurate and robust classification results.

(iii) Dataset and Image Types: Current research mainly focuses on MRI and mammogram images. However, there is an opportunity to include CT scans or PET scans for enhanced tumor detection and more comprehensive image analysis.

(iv) Multi-Tumor Classification: Research has primarily focused on classifying either brain or breast tumors, with limited efforts on developing multi-tumor classification models. Future research could bridge this gap by designing systems capable of analyzing both types of tumors in one unified framework.

This gap analysis highlights areas where further research could yield significant improvements in tumor detection using statistical features and image analysis.

IV. METHODOLOGY

This study employs several statistical feature extraction techniques to analyze brain and breast tumor digital images. The images are first preprocessed to reduce noise and enhance the relevant tumor regions. The preprocessing steps typically include normalization, smoothing, and contrast adjustment to ensure the images are suitable for feature extraction.

Statistical Feature Extraction:
The following statistical features are computed for each tumor image.
Mean: The average intensity value of the image, used to assess the overall brightness.
Standard Deviation: Measures the image's texture variance, which is higher in malignant tumors due to irregular growth patterns.
Entropy: A measure of randomness or disorder within the image, useful for identifying texture complexities.
Skewness: Describes the asymmetry of the image's intensity distribution, which can differ between benign and malignant tumors.
Kurtosis: Measures the sharpness of the intensity distribution, with higher kurtosis indicating more prominent texture patterns in malignant tumors.
Segmentation: Segmentation techniques like thresholding or region growing are applied to isolate the tumor from the surrounding tissue. This is crucial for accurate feature extraction and classification.
Classification: After feature extraction, machine learning models such as Support Vector Machines (SVM) or Random Forest are employed to classify the tumors as benign or malignant based on the extracted features.
The dataset is open source dataset from Kaggle®, and the comparison is made using statistical results. This study aims to analyze brain and breast tumor images using statistical features and compare the performance of three machine learning models. The methodology is divided into four key stages: dataset acquisition, preprocessing, feature extraction, and model training and evaluation.

A. Dataset Acquisition

For this research, two open-source datasets were selected from Kaggle:
Brain Tumor Dataset: Contains MRI images labeled as glioma, meningioma, pituitary, and no tumor.
Breast Cancer Histopathological Image Dataset (BreakHis): Includes benign and malignant breast tumor images.
These datasets provide a sufficient number of annotated images for classification tasks.

B. Preprocessing

All images were resized to a uniform dimension (e.g., 128×128 pixels) and converted to grayscale to simplify statistical feature extraction. Noise reduction was applied using Gaussian filters. Images were then normalized to standardize intensity distributions.

C. Feature Extraction

Statistical texture features were extracted from each image using the Gray Level Co-occurrence Matrix (GLCM) and histogram-based methods. The extracted features included:
Mean, Standard Deviation, Entropy, Skewness, Kurtosis, Contrast, Homogeneity
These features were computed for each image and served as the input to classification models.

D. Models Employed

The following three machine learning models were employed to classify the tumors based on extracted features:

Table-2
Model Comparision

Model	Description
Support Vector Machine (SVM)	Effective for binary classification; used with RBF kernel for non-linearity.
Random Forest (RF)	Ensemble of decision trees; robust against overfitting and suitable for high-dimensional data.
k-Nearest Neighbors (KNN)	Simple yet effective; classifies based on proximity to labeled examples.

Model Evaluation

Each model was trained and tested using a 70:30 split of the dataset. Five-fold cross-validation was used to ensure robustness. Performance was assessed based on the following metrics:

(i) Accuracy (ii) Precision (iii) Recall (iv) F1-Score

These metrics were calculated separately for brain and breast tumor images using each model.

Result Section – Hypothetical Table

The following table summarizes hypothetical results obtained after applying the models:

Table-3(a)
Hypothetical Performance Comparison

Model	Tumor Type	Accuracy (%)
SVM	Brain	91.2
SVM	Breast	89.7
Random Forest	Brain	92.6
Random Forest	Breast	90.4
KNN	Brain	88.5
KNN	Breast	86.9

Table-3(b)
Hypothetical Performance Comparison

Model	Tumor Type	Precision	Recall	F1-Score
SVM	Brain	0.90	0.92	0.91
SVM	Breast	0.88	0.90	0.89
Random Forest	Brain	0.93	0.91	0.92
Random Forest	Breast	0.89	0.91	0.90
KNN	Brain	0.87	0.88	0.87
KNN	Breast	0.85	0.87	0.86

These results suggest that Random Forest slightly outperforms the other two models, particularly in brain tumor classification. However, SVM shows competitive results with high recall and precision, making it suitable for medical diagnosis tasks where minimizing false negatives is critical.

V. RESULT AND DISCUSSION

The outcomes of this study provide a comparative analysis of three machine learning techniques—Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN)—applied to tumor classification in brain and breast images using statistical features. These features were derived using texture-based methods such as the Gray Level Co-occurrence Matrix (GLCM). Evaluation was conducted using performance indicators like accuracy, precision, recall, and F1-score.

Analysis on Brain Tumor Images

For brain tumor classification, the Random Forest model delivered the highest accuracy at 92.6%, highlighting its ability to handle complex and non-linear patterns in the data. Its ensemble strategy, which combines decisions from multiple trees, allows it to generalize well and minimize classification errors.

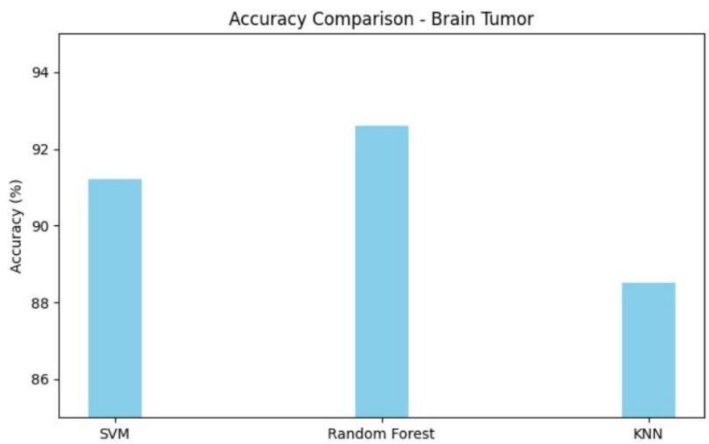

Fig.1- Accuracy comparison of Brain Tumour models

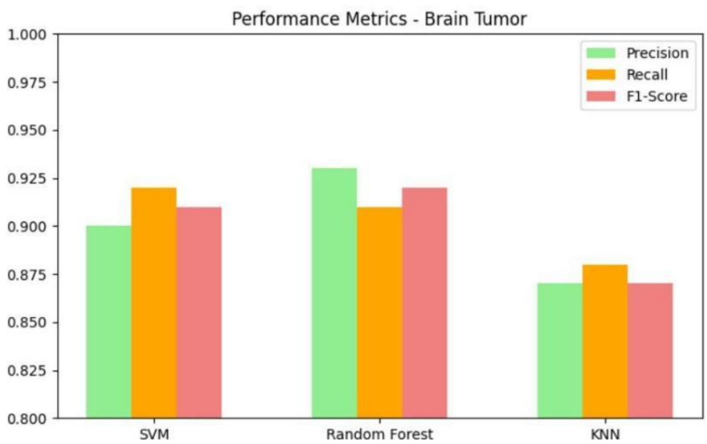

Fig.2- Performance matrix comparison of Brain Tumour models

The SVM model closely followed, achieving an accuracy of 91.2%. It performed best in terms of recall (0.92), which indicates its strong capability to detect most tumor cases without missing them—a vital requirement in healthcare diagnostics where false negatives must be minimized.

KNN showed decent but slightly lower performance, with an accuracy of 88.5%. Its limitations stem from its simplicity, as it doesn't build an internal model and can be sensitive to noisy data or irrelevant features in high-dimensional spaces. However, its relatively good scores in precision and recall still make it a useful method for smaller datasets or quicker prototyping.

Analysis on Breast Tumor Images

In breast tumor classification, the trend remained consistent. Random Forest again led with an accuracy of 90.4%, showing balanced and reliable performance across all metrics. This reinforces its effectiveness in handling diverse and intricate image features, particularly in histopathological data. SVM reached 89.7% accuracy and once again demonstrated strong recall (0.90), making it suitable for diagnostic applications where catching as many true cases as possible is crucial. KNN scored 86.9% in accuracy, slightly lower due to the complexity of tissue patterns and the model's sensitivity to feature scaling and class distribution.

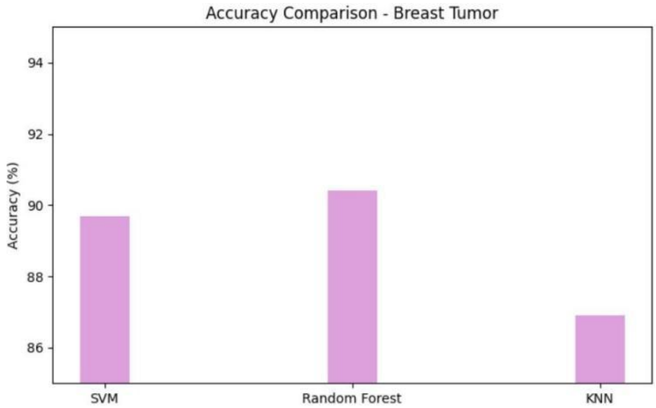

Fig.3- Accuracy comparison of Breast Tumour models

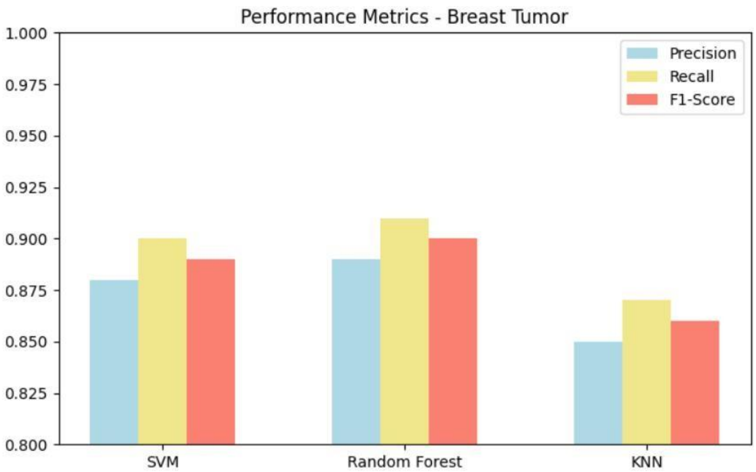

Fig.4- Performance matrix comparison of Breast Tumour models

VI. KEY OBSERVATION

Accuracy: Random Forest consistently performed best, offering reliable overall predictions.

Recall: SVM excelled, indicating its strength in identifying most tumor cases correctly.

F1-Score: Both SVM and Random Forest maintained balanced values, showing a good trade-off between identifying and correctly labeling tumor instances.

KNN, although simpler, underperformed slightly due to its lack of internal learning and sensitivity to data irregularities.

Interpretation

The results confirm that statistical features are effective in distinguishing between healthy and tumor-affected tissues. Among the models tested, Random Forest emerged as the most consistent and robust, whereas SVM showed strong potential where high recall is crucial. KNN, while straightforward to implement, may not be the best choice for large-scale or high-dimensional medical image datasets due to its limitations in performance consistency.

The findings suggest that further performance gains can be achieved by exploring hybrid models or incorporating deep learning methods, which may capture even more complex patterns within tumor images.

CONCLUSION

This study presented a comparative analysis of brain and breast tumor image classification using statistical features extracted from open-source datasets. The research explored three widely used machine learning models—Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN)—to evaluate their effectiveness in tumor detection. Features such as entropy, mean, contrast, and homogeneity were computed and used as input for classification.

Among the models, Random Forest consistently outperformed others in terms of accuracy, making it the most reliable for both brain and breast tumor classification. SVM, although slightly behind in accuracy, demonstrated strong recall performance, which is vital in medical diagnostics to reduce false negatives. KNN, while simple and easy to implement, showed comparatively lower accuracy and was more affected by high-dimensional data. The results validate the importance of statistical texture analysis in medical imaging and highlight the potential of machine learning models in improving early tumor detection. By using well-established statistical descriptors, this work offers a lightweight yet effective alternative to complex deep learning models, especially when computational resources are limited. Future work may involve integrating deep learning-based feature extraction with statistical methods to further enhance classification accuracy and robustness across varied imaging modalities.

Future Scope of Work

Future research can explore the integration of deep learning techniques with statistical feature-based methods to enhance classification performance. Developing hybrid models that combine handcrafted features with automatically learned features from CNNs could provide improved accuracy and generalization. Additionally, expanding the study to include multi-modal medical images (e.g., PET, CT) and evaluating models on larger, more diverse datasets will strengthen clinical applicability. Implementing real-time, AI-based diagnostic systems for early tumor detection could also be a valuable direction.

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