**ARTIFICAL INTERLLIGENCE AND MACHINE LEARNING[AIML]**

**ABSTRACT**

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**TITLE:**

Advanced Automated System for Detecting Brain Tumor Abnormalities in MRI Using machine learning

**BACKGROUND:** Accurate interpretation of MRI scans is essential for diagnosing and managing a wide range of medical conditions. Traditional methods of image analysis rely heavily on the expertise of radiologists, which can lead to variability in diagnostic outcomes and increased risk of error. There is a growing need for automated systems that can enhance diagnostic precision and efficiency in medical imaging.

**OBJECTIVE:** The objective of this project is to develop an advanced automated system that employs machine learning techniques to detect abnormalities in MRI scans. The system aims to provide radiologists with a reliable, efficient, and accurate tool for improving diagnostic accuracy and accelerating workflow.

**METHODS:**

1. **DATA ACQUISITION AND PREPARATION:**
   * **Dataset:**  Utilizes pituitary tumor MRI can images that publicly available dataset form Kaggle for brain tumor These datasets are annotated by expert radiologists and provide a diverse range of abnormalities.
   * **Preprocessing:** Images are preprocessed to reduce noise, normalize intensity, and augment data using techniques such as rotation, scaling, and translation to improve model robustness.
2. **MACHINE LEARNING MODEL DEVELOPMENT:**

**Algorithms:**

* **Support Vector Machines (SVM):** Employed for classification by finding the optimal hyperplane that separates the data into different classes. Different kernels such as linear, radial basis function (RBF), and polynomial are evaluated for the best classification performance.
* **Feature Extraction:** Features are extracted from the images using methods like Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) to reduce the dimensionality before feeding them into the SVM for classification.

**Training:** The model is trained using a supervised learning approach with a training dataset and validated using a separate validation dataset. Cross-validation techniques are applied to ensure the model generalizes well to unseen data, and hyperparameters like the regularization parameter (C) and kernel parameters (gamma, degree) are tuned for optimal performance.

1. **SYSTEM INTEGRATION:**

**User Interface:** A user-friendly interface is designed for radiologists to interact with the system. Features include automated anomaly detection and visualization of detected abnormalities.

**Tools Used:** Python programming with libraries such as numpy , pandas ,sklearn for model development; OpenCV for image processing; streamlit for web-based interface development.

1. **PERFORMANCE EVALUATION:**

**Metrics:** Evaluated using accuracy, sensitivity and specificity.

**Validation:** Cross-validation is performed to assess the model's effectiveness.

1. **CONTINUOUS LEARNING AND IMPROVEMENT:**
   * **Feedback Mechanism:** Integrated to refine the model based on real-world usage and user feedback. This includes periodic retraining with new data and adapting to evolving diagnostic standards.