WorkFlowIQ: AI-Driven Smart Task Scheduling System

***Abstract*—WorkFlowIQ is an advanced AI-driven task scheduling system designed to optimize workflow efficiency and resource utilization in dynamic environments. By leveraging machine learning and artificial intelligence algorithms, WorkFlowIQ intelligently analyzes task dependencies, resource availability, and temporal constraints to generate optimal schedules for teams, individuals, or systems. The system adapts to changes in real-time, ensuring that workflows are continuously optimized, even under unpredictable circumstances. WorkFlowIQ integrates seamlessly with existing project management tools and organizational infrastructures, offering automated scheduling, task prioritization, and conflict resolution. This results in reduced operational overhead, enhanced productivity, and more efficient task management. The system can be deployed across various industries, including software development, manufacturing, logistics, and service operations, providing significant time and cost savings while enhancing decision-making processes.**

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**Introduction**

In today's fast-paced and ever-evolving work environments, efficient task scheduling is critical to optimizing productivity and ensuring smooth operations. Traditional task management methods often struggle with handling complex dependencies, unexpected changes, and resource limitations, leading to delays, inefficiencies, and missed opportunities. The advent of artificial intelligence (AI) offers promising solutions to these challenges, enabling systems to dynamically adapt and optimize workflows in real-time.

WorkFlowIQ is an AI-driven smart task scheduling system designed to address the shortcomings of conventional scheduling approaches. By harnessing advanced machine learning techniques, WorkFlowIQ intelligently analyzes a variety of factors such as task priority, resource availability, inter-task dependencies, and temporal constraints. It then generates optimal schedules that maximize efficiency while minimizing bottlenecks and conflicts.

What sets WorkFlowIQ apart is its ability to continuously learn and adapt based on new data, ensuring that schedules remain efficient even in the face of changing priorities, unexpected events, or fluctuating resource availability. Whether for teams, individuals, or automated systems, WorkFlowIQ is capable of managing workflows across multiple industries, including software development, manufacturing, logistics, and service operations.

This system not only simplifies the process of task scheduling but also enhances decision-making, offering organizations the ability to allocate resources effectively, meet deadlines, and improve overall productivity.

**Related Works**

, from traditional rule-based scheduling systems to modern AI-powered solutions. Below are some of the key areas and works related to the development of smart task scheduling systems, which provide a foundation for the development of WorkFlowIQ.

**Traditional Scheduling Algorithms and Systems** Early task scheduling systems were based on classical algorithms such as First Come First Served (FCFS), Shortest Job Next (SJN), and Round Robin. These systems are typically static and lack the flexibility to adapt to real-time changes in workload, resource availability, or priority shifts. While these methods can be efficient in certain controlled environments, they are ill-equipped for dynamic and unpredictable work environments where resource constraints and task dependencies are complex.

**Constraint-Based Scheduling** Several approaches have been developed to address complex scheduling problems using constraint-based optimization techniques. These systems model tasks and resources as mathematical constraints and solve them using algorithms such as linear programming, constraint satisfaction problems (CSP), or integer programming. Works like "Constraint-Based Scheduling: A Comprehensive Survey" (Hunsberger & Roussopoulos, 2013) focus on applying constraint satisfaction in scheduling tasks, primarily in manufacturing and production environments. These systems ensure that schedules meet predefined rules but often lack the ability to adapt dynamicallytonew data or unforeseen disruptions

**Machine Learning-Based Scheduling** The integration of machine learning (ML) into scheduling systems has gained traction in recent years. ML models can predict task durations, optimize resource allocation, and adjust schedules based on historical data. "A Machine Learning-Based Scheduling System" (Li et al., 2018) presents an intelligent scheduling approach for manufacturing processes using historical data to forecast task durations and allocate resources more effectively. These models can enhance efficiency and predict task completion times, but they generally rely on static datasets and are often limited in their ability to adapt to real-time operational changes.

**AI-Driven Dynamic Scheduling Systems** Several AI-driven systems have emerged that focus on dynamically adapting task schedules based on real-time data and environmental changes. One such system is the "AI-Based Dynamic Task Scheduling" algorithm developed by Dufresne and colleagues (2020), which uses reinforcement learning (RL) to optimize task scheduling in cloud computing environments. By leveraging RL, the system continuously learns from its past decisions to make more informed scheduling choices and adapt to resource changes in real time. These systems, while advanced, can be computationally expensive and typically focus on specific domains like cloud computing or data centers.

**Multi-Agent Systems for Task Scheduling** Multi-agent systems (MAS) have also been explored for task scheduling, especially in decentralized environments where multiple autonomous agents must collaborate to complete tasks. In works like "A Multi-Agent Approach for Task Scheduling in Distributed Systems" (Vidal et al., 2015), agents represent individual tasks or resources, and they cooperate or compete to generate optimal schedules. These systems work well in environments where tasks are distributed across multiple agents or systems, such as in logistics or project management, but they often require complex communication protocols and are not always scalable for large organizations.

**Smart Scheduling in Project Management** In the realm of project management, tools like Microsoft Project and Primavera have integrated basic scheduling capabilities, including dependency management and critical path analysis. However, these systems often lack real-time adaptability and fail to optimize resource usage or predict potential bottlenecks. A significant advancement in this area is the work by Dutta and Babu (2019), which applies AI to project scheduling to improve resource allocation, risk management, and timeline predictions. These tools incorporate machine learning to predict the likelihood of delays based on historical project data, helping project managers make better-informed decisions.

**AI-Enhanced Workflow Automation** Workflow automation platforms like Zapier, Asana, and Monday.com have increasingly included smart scheduling features. For example, Asana’s "Workload" feature allows users to track resource allocation, and Monday.com offers automations that streamline task management processes. However, these tools often rely on rule-based systems or pre-defined templates, limiting their adaptability. WorkFlowIQ differentiates itself by using advanced AI algorithms to continuously adapt and optimize task schedules in real-time based on changing project dynamics, something that existing systems generally lack.

**Predictive Scheduling and Analytics** Predictive scheduling has been explored as a means to enhance task management through the use of historical data and forecasting techniques. In healthcare and retail, for example, predictive scheduling models help optimize employee shift planning by anticipating demand and adjusting schedules to reduce overstaffing or understaffing. "Predictive Analytics for Scheduling and Task Management" (Sharma & Gupta, 2020) reviews the use of predictive models to enhance workforce scheduling.

**Literature Survey**

Task scheduling has been an area of research and development for decades, with applications spanning various fields, including manufacturing, logistics, software development, and project management. Traditional methods of task scheduling have evolved from simple rule-based systems to more complex AI-driven solutions. This literature survey examines key advancements in task scheduling and identifies areas where WorkFlowIQ can make significant contributions.

**Traditional Task Scheduling Methods**Early research in task scheduling focused on basic algorithms such as First-Come, First-Served (FCFS), Shortest Job Next (SJN), and Round Robin. These methods, discussed in works like **"Computer Systems Performance Evaluation" by Hwang and Briggs (1984)**, are straightforward and efficient in controlled environments but often fail to optimize complex, dynamic workflows. These traditional methods assume static conditions where task priorities and resource availability do not change, which limits their applicability in real-world, fast-paced environments.

**Constraint-Based Scheduling Systems**Constraint-based scheduling systems are designed to manage complex task dependencies and resource constraints. These systems represent tasks and resources as a set of mathematical constraints, which are then solved using optimization algorithms like Linear Programming (LP) or Constraint Satisfaction Problems (CSP). In **"Constraint-Based Scheduling: A Comprehensive Survey" (Hunsberger & Roussopoulos, 2013)**, the authors present a broad overview of constraint-based systems, which are common in manufacturing and production planning. While such methods ensure that schedules comply with predefined rules, they typically lack the flexibility to adjust dynamically to changing conditions, making them less effective in environments where resource availability or task priorities shift unexpectedly.

**Machine Learning for Task Scheduling**Recent advancements have introduced machine learning into task scheduling, aiming to predict task durations, resource allocation, and potential delays. **Li et al. (2018)** in **"A Machine Learning-Based Scheduling System"** present a model for manufacturing that uses historical data to predict task durations and optimize resource allocation. Machine learning offers greater flexibility and predictive capabilities compared to traditional methods. However, most of these systems rely on historical data and may struggle to adapt in real-time to significant disruptions or unforeseen events, as they tend to work with relatively static models rather than continuously evolving schedules.

**AI-Driven Dynamic Scheduling Systems**AI-driven dynamic scheduling systems, particularly those that employ reinforcement learning (RL) or other adaptive algorithms, have garnered attention in areas like cloud computing and network management. **Dufresne et al. (2020)** discuss **"AI-Based Dynamic Task Scheduling"** using RL algorithms to optimize scheduling in cloud environments. These systems can learn from past decisions and continuously adapt to changing conditions, such as task delays or resource reallocation. While these models provide greater adaptability, they are often computationally expensive and focus on niche areas such as cloud computing or large-scale data centers. These models are not always generalized to broader task scheduling problems in industries like manufacturing or project management.

**Multi-Agent Systems for Task Scheduling**In decentralized environments, multi-agent systems (MAS) have been proposed to solve scheduling problems where multiple autonomous agents must cooperate to complete tasks. **Vidal et al. (2015)** discuss **"A Multi-Agent Approach for Task Scheduling in Distributed Systems"**, where agents represent tasks or resources, and they must communicate and negotiate to find an optimal schedule. While MAS is effective in environments where tasks are distributed across various agents (e.g., logistics, distributed computing), it often requires complex communication protocols and is typically less efficient for tasks within a centralized environment, such as those in a single organization or project.

**Predictive Scheduling and Analytics**Predictive analytics has become a key component of modern scheduling systems, especially in industries like healthcare, retail, and project management. **Sharma and Gupta (2020)** in **"Predictive Analytics for Scheduling and Task Management"** explore the use of predictive models to enhance workforce scheduling, especially in retail environments. By predicting demand fluctuations and adjusting schedules accordingly, predictive models ensure that resources are optimally allocated. However, these models often focus on a specific domain and are not designed to handle the complexity of interdependent tasks or the dynamic changes in multi-task environments, such as those found in software development or manufacturing.

**Workflow Automation Platforms**Many project management tools, such as **Asana**, **Trello**, and **Monday.com**, have started incorporating workflow automation features, including basic task scheduling and resource allocation. **"Workload Management in Collaborative Project Management"** (Jiang et al., 2018) highlights how tools like Asana help visualize task allocation and optimize resource usage. However, these tools often rely on rule-based scheduling and lack the ability to predict or respond to unexpected changes in real-time. They are also limited by pre-defined templates and rules, which make them less adaptable to highly dynamic environments.

**Hybrid Models Combining AI and Traditional Methods**A promising direction in task scheduling research is combining traditional optimization techniques with AI to create hybrid models. **Dutta and Babu (2019)** in their work **"AI-Enhanced Project Scheduling"** combine AI methods with classical project management techniques, such as Gantt charts and Critical Path Method (CPM), to enhance decision-making in project scheduling. This hybrid approach combines the strengths of traditional project management methods with the predictive power and adaptability of AI, offering a more flexible solution. However, while promising, these hybrid models often still fall short of real-time dynamic adaptation, especially in complex or unpredictable environments.

**WorkFlowIQ’s Position in the Landscape**WorkFlowIQ aims to bridge the gap between traditional task scheduling systems, machine learning-based models, and AI-driven dynamic scheduling systems. Unlike constraint-based systems or rule-based scheduling tools, WorkFlowIQ’s AI engine continuously learns and adapts based on real-time data, making it capable of handling dynamic environments with task interdependencies and changing resource availability. While predictive analytics and machine learning offer valuable insights, WorkFlowIQ differentiates itself by providing real-time task rescheduling, predictive risk management, and continuous workflow optimization, ensuring that schedules evolve as projects progress. It also integrates seamlessly with existing project management platforms, offering an accessible, scalable solution for a variety of industries, from software development and manufacturing to logistics and healthcare.

**Proposed System**

The proposed system, **WorkFlowIQ**, is an intelligent task scheduling solution designed to optimize task management, resource allocation, and workflow efficiency through the use of artificial intelligence (AI) and machine learning (ML). It is a dynamic, adaptable system that continuously adjusts to changes in tasks, resources, and priorities, providing real-time insights and recommendations for task scheduling. Unlike traditional, static scheduling systems, WorkFlowIQ learns from past performance, predicts potential bottlenecks, and ensures tasks are completed on time with optimal resource utilization. Below is a detailed breakdown of the proposed system, its components, and functionality.

**System Overview** WorkFlowIQ aims to address the challenges of managing complex workflows in dynamic environments where task priorities, deadlines, and resources can change unexpectedly. The system uses AI to analyze and optimize task scheduling across multiple dimensions, such as task dependencies, resource availability, and time constraints. By doing so, it helps organizations minimize delays, reduce resource wastage, and improve productivity. The system is designed for scalability, making it suitable for small teams, as well as large organizations managing complex workflows.

**System Architecture**WorkFlowIQ operates on a **cloud-based architecture**, allowing it to be accessed from anywhere, ensuring scalability and flexibility. It employs a **centralized AI engine** that analyzes all incoming data and optimizes scheduling decisions in real time. This engine interfaces with a **user-friendly front-end dashboard**, where project managers and team members can interact with the system, view visualizations, and make adjustments as necessary. **APIs** enable integration with third-party tools to streamline workflows and enhance collaboratio

**Dynamic Scheduling and Resource Allocation**WorkFlowIQ automatically adjusts task schedules and resource assignments in response to changing conditions, ensuring optimal performance across tasks and resources. This minimizes disruptions and prevents delays caused by unforeseen issues.

**AI-Driven Predictions**The system uses AI and machine learning to predict task durations, resource utilization, and potential delays, ensuring better planning and reducing the chances of project overruns.

**Real-Time Task Rescheduling**f there are changes in task execution (e.g., delays, resource unavailability), WorkFlowIQ automatically reschedules tasks and reallocates resources, making the system highly adaptable in fast-paced environments.

**Enhanced Risk Management**The predictive analytics engine helps identify potential risks and bottlenecks before they occur, enabling project managers to take corrective actions before issues escalate.

**Integration with Existing Tools**WorkFlowIQ integrates seamlessly with existing project management tools such as Jira, Trello, Asana, and Microsoft Project, allowing users to leverage the system without disrupting their current workflow.

**Scalability and Flexibility**The system is scalable, capable of supporting both small teams and large organizations. It can adapt to various industries, including software development, manufacturing, logistics, and more.

**AI-Powered Scheduling Engine**The core of WorkFlowIQ is its **AI-powered scheduling engine**, which utilizes machine learning algorithms to create and continuously refine task schedules based on real-time data. This engine is designed to

Real-Time Adaptation and ReschedulingWorkFlowIQ incorporates a real-time adaptation and rescheduling mechanism that allows it to respond to changes on-the-fly. For example, if a critical resource becomes unavailable or a task is delayed due to unforeseen circumstances, the system automatically:

Predictive Analytics and Risk ManagementThe system leverages predictive analytics to forecast potential risks or bottlenecks that could impact the project’s timeline. For example, if there is a high likelihood that a resource will be unavailable or a task will be delayed, the system flags these potential risks and suggests corrective actions. It can also predict:

User-Friendly Interface and VisualizationsWorkFlowIQ provides a highly intuitive user interface that allows users to view and interact with their task schedules. The interface includes:

The proposed system aims to address the existing challenges by introducing a streamlined, efficient solution that integrates advanced technologies to improve overall performance. It will leverage cutting-edge tools and methodologies to automate and optimize processes, reducing manual intervention and enhancing operational efficiency. The system will be user-friendly, ensuring seamless interaction for end-users while maintaining high levels of security and data integrity. Through real-time analytics and robust decision-making capabilities, it will offer valuable insights for continuous improvement. Ultimately, this system will significantly reduce costs, increase productivity, and foster innovation, making it a vital asset for the organization or project.

In addition to operational efficiency, the system emphasizes enhanced user experience, offering intuitive interfaces and streamlined workflows. This ensures a minimal learning curve for users while maintaining a high level of performance. Security is a top priority, and the system will incorporate advanced encryption, multi-factor authentication, and compliance with industry standards to safeguard sensitive information. By fostering collaboration and communication across departments, the system will enable better coordination, reducing silos and improving overall organizational synergy.

Furthermore, the proposed system is designed to be cost-effective, with long-term benefits that outweigh the initial **investment. By** reducing errors, minimizing downtime, and optimizing resource allocation, the system will lead to substantial savings. It will also promote sustainability by leveraging energy-efficient technologies

trained by data augmentation to overcome the lack of data problem. A neural network-based approach for multi-grade brain tumor classification (CNN). CNN’s are feed-forward artificial neural networks (ANNs) that use natural ways to recognize patterns in images. Data augmentation improves the accuracy of the radio media dataset. Following data augmentation, the dataset's sample count was increased from 3064 to 91920. Using data augmentation techniques,

30 additional photographs are produced from a single example image. The VGG-19 architecture's first two convolution layers are followed by max-pooling, as seen in each MR image, and the same combination is repeated for the next two layers. The accuracy of the radiopaedia dataset for grades I, II, III, and IV is 90.03 percent, 89.91 percent,

84.11 percent, and 85.50 percent, respectively. The results were convincing enough to be employed in real-world applications after completing data augmentation on both datasets. Grade I accuracy improved from 90.03 percent to

95.5 percent utilizing this dataset. Similarly, accuracies in grades II, III, and IV have increased from 89.91 percent to

92.66 percent, 84.11 percent to 87.77 percent, and 85.50 percent to 86.71 percent, respectively.

Alagarsamy et al. [14] utilize a deep learning method to segment and recognize brain tumors, a continuous deep learning-based feature selection technique is required. For deep feature extraction in the classification step, the Inception V3 pre-trained CNN model is used. With an average accuracy of more than 92 percent, the categorization approach is used on BRATS2013, 2014, 2017, and 2018.

Sikka et al. [5] performed the preprocessing, feature extraction using a 2-D Discrete Wavelet Transform, feature reduction using colour moments, and classification using a feed-forward neural network were the four major aspects of the proposed system.

Chen et al. [6] used the Neutrosophy-convolution neural network hybrid technique is used in the proposed system (NS-CNN). CNN was utilized to extract features from segmented brain images, which were subsequently classified using SVM and KNN classifiers in the classification step. CNN features fared better in classification with SVM. With an average success rate of 95.62 percent, the output data was confirmed.

Farhi et al. [7] used the CNN-based deep learning (DL) model to beat the six types of ML models in five types of multiclass tumor datasets. Two-, three-, four-, five-, and six- class data are the five sorts of data. The AI system based on transfer learning beats machine learning techniques in grading multiclass brain tumors.

Sun et al. [8] proposed the usage of Residual Networks to improve brain tumor categorization. The ResNet50 architecture is a 50-layer variant of the Residual Network. A stochastic optimization technique with a learning rate of.00001, was used to train our model across 500 epochs.

Unlike the convolutional neural network, the capsule neural network is made up of capsules that house a collection of

neurons [22]. The activity vectors in the capsules reveal a specific entity type parameter that is used for instantiation, which could be a component of a whole object or an object in its entirety. It might also be stated in terms of computer graphics, which uses a transformation matrix to break down the entire task into smaller chunks. The capsule network, on the other hand, uses the inverse matrix to transform a single position of an entire task into a position of a complete task.

The Gabor wavelet Transform is used in the intended approach to eliminate noise information while retaining the edges [23]. To separate the same characteristics into a limited set of groups, the K-means process is utilized. The suggested technique includes the Fuzzy c means clustering of pictures to represent the attributes of the images in the form of histogram properties.

Using a dual-force training technique, [7] introduced the MLDeepMedic and U-Net CNN models. In order to acquire more abstract semantic information, this training technique entails adding an auxiliary classifier to their high-level convolutional layers. Deep Medic's model has been enhanced to Multi-Level Deep Medic, which segments data more precisely using multi-level data. For categorization, the two most recent brain tumor datasets, BRATS 2017 and BRATS 2015, were used. Dual-Force Networks are CNNs that use this training technique (DFNs). The Multi-Layer Perceptron post-processing approach can improve segmentation performance by improving CNN prediction outputs. To optimize all networks, use the Stochastic Gradient Descent method.

1. Proposed Methodology

# . Pro po sed system

Create a deep learning model. The pipeline is broken down into various stages, starting with the receiving of raw data and ending with the system classification output [9]. The following are the phases of the proposed system:

* + Preparing the data
  + Morphological Procedures
  + Segmentation of images
  + Extraction of Features
  + Categorization

1. Pre-Processing:A series of techniques applied to a scanned input image is known as pre-processing.Pre- processing separates the fascinating pattern 19 from the background by removing the undesirable data from the scanned images.
2. Morphological Procedures Morphological Image Processing is a collection of non-linear image processing algorithms that deal with the shape or structure of image features.
   1. Sobel Edge and Markers are the steps involved in the Morphological procedures.
   2. Threshold for Inverse Binarization
   3. Reconstruction Closure
   4. Binary criterion
3. Image Segmentation: Image segmentation is the process of dividing a picture into many parts in order to make it easier to analyze and interpret. Watershed segmentation was applied in this case [11].

Image segmentation is a technique to split the image into multiple parts. The main objective of this separation is to facilitate the study and interpretation of images while preserving their quality. This technique is also used to trace the edges of objects in images. This technique labels pixels by their intensity and characteristics. These parts represent all the original images and acquire their characteristics such as intensity and likeness. Image segmentation helps create a 3D contour of the body for brain tumor detection. Segmentation is used in machine perception, malignant disease analysis, tissue volumes, anatomical and functional analyses, 3-D rendering techniques., virtual reality visualization and anomaly analysis, and object definition and detection.

1. Feature Extraction: Feature extraction is the process of reducing the number of requirements required to describe the actual data in an effective manner. The contour is drawn using a segmented picture [12]. The algorithm analyses the relevance section by using the range values as the threshold, using the firmware evaluation method from a fragmented image.

# Neural Network with Convolution

Convolution and pooling are the two layers that make up the convolution base. The parameters are taken from the dataset's photographs. CNN classifiers are made up of fully linked layers that use characteristics acquired from the convolution layer to categorize images [13].

* 1. Dataset Acquisition

The dataset was used to identify items and evaluate the recognition system's performance throughout the training phase. A database is used to collect images of brain tumors. Photographs of both healthy and sick persons are gathered. The Joint Photographic Experts Group format is used to save all of the samples [14].

* 1. Layer of convolution

The network has been tuned to recognize the plant. Convolution layer. The features of an input brain image are acquired by the first layer of CNN [15]. Using brain data to establish the link across pixels using image feature information. It has two inputs: an image matrix and a kernel. An image in a convolution layer performs processes such as blurring with various filters and edge detection. The feature map was produced by the hidden layers after the convolution layer. It has the same weight and is biased in the same way. During the training of the network, the weights can be varied. By learning image features, the values can be assigned depending on the pixels [16].

* 1. Training Phase

The data source is being used to train CNN. 90% of the images in the dataset have been used in the training phase, with the remaining images being taken for validation and testing [17].

Image Preprocessing-The images are preprocessed with high definition and an object of Interest is selected throughout the learning process to distinguish the brain tumor images from their surroundings [18]. To minimize the training time, the image size was reduced.

Image Augmentation - This technique is used to enlarge the dataset. During the training phase, the network might learn more features from the image [19]. To increase the dataset, several modifications were used to the training dataset. The perspective transformation and The Image Net dataset were used to train the CNN. A new class relevant to brain tumor disease diagnosis may be incorporated instead of the original classifiers when a pre-trained model is applied [20]. The weights that have been allocated to each stratum. There are three types of pre-trained models.

1. Continue to progress the unified model
2. Raise a few layers while allowing the others alone.
3. Frost the base of the convolution.



Pooling layer

Convolutional layer

Fully Connected

layer

Image Classification

Activation Function

Fig.1 Image Classification technique for Brain Tumor Image classification using CNN.

# Pooling Layer

Down selection of brain tumor images is accomplished using pooling layers. It fetches the image from the backward convolution layer and reduces the size of the dataset while keeping the relevant data about the brain tumor section. For

down sampling, max-pooling selects the largest element from the feature map.

# Fully Connected layer

Before being placed in a fully linked layer, the picture from the max-pooling is normalized into a vector. The feature matrix generates a vector. By combining all of the pieces, a network model is created. Finally, the outputs were categorized as diseased brain image, healthy brain image, and disease category using the activation function.

# Testing Stage

During the testing phase, a representative image is provided to the convolution layer to be tested.The image is processed using a convolution layer. The image should be convoluted, and the matrix in the convolution layer should be activated with ReLU.Using its feature map, the testing sample brain images are coupled with the trained sample.The pooling layer receives the final convolution layer outcome, which is tangled by the outputs of numerous convolution layers [21]. To lower the size of the dimensionality, pooling is used in the pooling layer.

# Output layer

Using the sigmoid activation function, the output layer divides brain pictures into healthy and unhealthy categories. For two methods of classification, the sigmoid function was used [22]. As a result, we propose that the softmax activation function be used. Using brain images, the softmax activation function has been utilized to classify different types of diseases [24].

1. Results and Discussion

A dataset of 150 images from Kaggle is used to assess the efficiency of the suggested approach. 150 of them are tumor photos that are positive. Experiments were carried out with segmentation and a KNN classifier, yielding the following findings.

Table 1: Classification of Meningioma

|  |  |  |  |
| --- | --- | --- | --- |
| Result | | Predicted Positive | Predicted Negative |
| Actual  Value | Actual  Positive | TP=50 | FN=0 |
| Actual  Negative | FP=1 | TN=49 |

Table 2: Classification of Glioma

|  |  |  |  |
| --- | --- | --- | --- |
| Result | | Predicted Positive | Predicted Negative |
| Actual  Value | Actual  Positive | TP=49 | FN=1 |
| Actual Negative | FP=2 | TN=48 |

Table 3: Classification of Pituitary

|  |  |  |  |
| --- | --- | --- | --- |
| Result | | Predicted Positive | Predicted Negative |
| Actual  Value | Actual  Positive | TP=50 | FN=0 |
| Actual Negative | FP=1 | TN=49 |

The table.1 represents the classification accuracy of Meningioma, table.2 represents the classification accuracy of Gliomas and table.3 indicates the classification accuracy Pituitary tumors. Among 150 images each 50 belongs to Meningioma, Glioma, and Pituitary. For each case, 100 images are considered, with 50 tumors that are positive of

one kind and 50 tumors that are negative of another type, as well as negative tumor images.

# Accuracy rate

The following formula is used to find the matching rates after the table values have been calculated.

Accuracy (A) = (TP + TN) / (TP + FN + FP + TN) (1)

Sensitivity (S) = TP/ (TP + FN) (2) Precision (P) = TP/ (FP + TP) (3) Specificity SP = TN/ (FP + TN) (4)

True Positive, False Positive, False Negative, and True Negative are represented by TP, FP, FN, and TN, respectively. The methods presented can be used to

calculate the categorization accuracy rate for each type.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Brain Tumor MRI Images** | **Brain Tumor Classifi cation** | **Sensitivity(**  **%)** | **Precision(**  **%)** | **Specificity(**  **%)** | **Accura cy (%)** |
|  | Meni  ngio ma | 100 | 98 | 98 | 99 |
|  | Glio  ma | 98 | 96 | 96 | 97 |
|  | Pituit  ary | 100 | 98 | 98 | 99 |

Fig.2 Results of proposed method for three forms of brain tumour classification. (Meningioma, Glioma, Pituitary)

1. Conclusion

Deep Learning is being used to improve disease. Identification and classification. CNN has been trained using ReLu. CNN's convolution base utilizes convolution and pooling layers to extract features from images. The CNN classifier separates the image into categories based on characteristics gathered from the convolution basis. classifiers. During the pre-trained model's training phase, 80% of the dataset will be utilized. The remaining 80% of the dataset will be used in the testing phase. As a result, the network may be trained to perform a wide range of tasks. The use of CNN and deep learning to classify brain tumors and predict accurate outcomes.

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