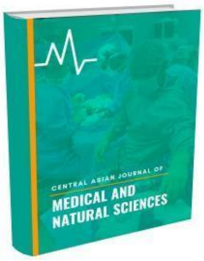

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Article

InceptiNeuro-V2B1: A Hybrid Transfer Learning Framework for Real-Time Brain Tumour Detection and Classification

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Abstract: Detecting brain tumors is still a big problem in medical diagnostics. This is made even harder by the fact that there aren't many labeled datasets, MRI imaging quality varies, and high diagnostic accuracy is needed in clinical situations where time is of the essence. Conventional manual diagnosis is time-intensive and prone to observer variability, whereas independent deep learning models frequently encounter generalization challenges, especially within limited and imbalanced medical datasets. To tackle these challenges, this study presents InceptiNeuro-V2B1, a hybrid transfer learning-based CNN system for accurate and instantaneous brain tumor classification. The suggested approach utilizes MobileNetV2 as a pre-trained foundational model, meticulously adjusted to differentiate between glioma, meningioma, pituitary tumors, and normal brain scans, employing sophisticated preprocessing and real-time data augmentation techniques. The model is part of a web app built on Flask that lets users upload MRI images directly and get real-time predictions on tumors. Using a public brain MRI dataset for evaluation, Inceptineuro-V2B1- V2B1 got a test accuracy of 95.1% and high precision, recall, and F1-scores for all types of tumors. The system guarantees strong performance even on imbalanced datasets by using transfer learning, a lightweight architecture, and clinical usability. InceptiNeuro-V2B1 is a decision-support tool for real-world medical settings that is scalable, ready to be deployed, and efficient. It improves early diagnosis and treatment planning in neuro-oncology.

Keywords: Convolutional Neural Networks, Transfer Learning, Advanced Architectures, Keras Deep Learning, Random Noise, Treatment Planning, Local Features, Pre-Existing Knowledge

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1. Introduction

Finding brain tumors is still one of the most difficult and long-lasting problems in modern medical diagnosis. Brain tumors are dangerous to people all around the world, and the effectiveness of their treatment depends a lot on finding them early and correctly [49]. Neuroimaging technologies like Magnetic Resonance Imaging (MRI) have come a long way in the last several decades. MRI is now an important tool for finding and assessing brain problems since it lets you see soft tissues in great detail. But even if imaging techniques have gotten better, manually analyzing MRI data is still a lot of work, takes a long time, and is prone to mistakes [74]. Radiologists must carefully look at hundreds of picture slices to find possible tumor areas, figure out their edges, and figure out how far along they are in their growth [66]. This manual method is not only subjective, but it is also open to human weariness and prejudice in interpretation, which can lead to diagnoses that are not consistent. As a result, the medical field is still looking for reliable automated technologies that can improve the accuracy and speed of diagnosing brain tumors early on.

Brain tumors pose a significant risk to human health, frequently resulting in neurological deficits, disability, and death if not identified or managed appropriately [56]. The intricate architecture of brain regions, along with the diverse characteristics of tumors, poses significant hurdles for detection and therapy. Brain tumors can be either malignant or benign, and it is very important to know which type they are in order to decide on the best course of action. Malignant tumors, like gliomas, are very aggressive and need to be treated very away. Benign tumors, such as meningiomas, are not as harmful, but they can still create major problems by putting pressure on nearby brain regions. An MRI scan is usually the first step in the diagnosing procedure. Then, a radiologist looks at the pictures and looks for problems with tissue density, contrast enhancement, or shape [79]. But this approach relies on the knowledge and experience of medical professionals, and in areas where neurologists or advanced healthcare facilities are hard to find, it becomes harder to find problems quickly [82]. Without reliable and quick diagnostic techniques, treatment may not start right away, which makes it less likely that the patient will fully recover.

The use of artificial intelligence (AI) and machine learning (ML) in medical imaging has changed the way doctors diagnose diseases by making the process more automated, accurate, and scalable [81]. Deep learning models, especially convolutional neural networks (CNNs), have been very useful for tasks that include images, like classification, segmentation, and object detection. Deep learning models are trained on huge sets of MRI scans to understand patterns and traits that set normal brain tissue apart from diseased brain tissue [58]. This is done in the context of finding brain tumors. Deep learning algorithms automatically extract hierarchical representations of data, capturing complex visual signals and small differences that may not be easily detectable to the human eye. This is different from standard image processing approaches that rely on manually created features [75]. AI-based systems can do diagnostic tasks with amazing accuracy because they can learn and generalize from huge volumes of data. In fact, they often do better than expert radiologists.

The goal of creating an automated brain tumor detection system is to cut down on the time it takes to make a diagnosis, reduce mistakes made by people, and help doctors make decisions in the clinic [48]. A system like this can be a reliable second opinion by automatically finding tumor areas, making sure that no important indicators are missed. The suggested system's goal is to sort MRI images into two groups: those that show a tumor and those that don't [78]. It can also be used to find certain types of tumors, such glioma, meningioma, or pituitary tumors, by looking for visual features that have been learned [65]. This classification feature is quite useful for helping radiologists at the beginning of the diagnosis process. It lets them focus on arranging treatment instead of finding the problem. Automated methods also make it easier to screen big groups of people, especially in healthcare settings where there aren't many radiologists or where there are too many patients for each specialist.

The main goal of building a brain tumor detection model based on deep learning is to improve the accuracy and dependability of diagnoses. Early and accurate identification of tumor locations not only enhances the likelihood of effective treatment but also alleviates the psychological and financial burdens on patients and healthcare systems [55]. The model should be able to quickly evaluate MRI scans, find areas of the brain that are not normal, and sort them by whether or not a tumor is present and what type it is [73]. Also, it tries to cut down on the need for manual analysis, make the diagnostic process more efficient, and make sure that results are the same no matter how skilled or experienced the operator is [67]. The initiative aims to increase diagnostic accuracy by using complex computational methods, while yet making it easy for users to understand and for clinicians to interpret. Putting these kinds of tools into existing medical systems can help doctors make decisions in real time and cut down on the time it takes to start therapy after a diagnosis.

The project is based on medical imaging and artificial intelligence, and it uses ideas from computer vision, pattern recognition, and biomedical engineering. It entails the methodical examination of MRI images to identify salient markers that delineate the structural and textural disparities between healthy and neoplastic brain tissues [50]. Deep learning is used in this field so that the system can learn from a lot of medical data and get better at its job as more images are added. These systems use neural network topologies that act like the human brain to recognize complicated visual patterns. This makes them quite good at finding even little or oddly shaped tumors [64]. The method also stresses generalization, which is the model's ability to work well on data it hasn't seen before. This is very important for using the model in a variety of clinical settings in the real world [69]. The integration of deep learning and medical imaging signifies a notable progression in diagnostic automation, reconciling human competence with computational intelligence.

The project encompasses various aspects of medical picture analysis and diagnostic assistance [53]. It includes building a complete system that can find and classify brain tumors from MRI data with little help from people. The method has a number of important steps, starting with collecting and preparing data, which means standardizing raw MRI images, reducing noise, and enhancing areas of interest [70]. Deep learning models that automatically learn how to tell the difference between images are then used to extract features. During the training phase, the model is shown labeled datasets so that it can tell the difference between normal and abnormal samples. After training, the model is tested and tweaked to make sure it is as accurate, sensitive, and specific as possible [60]. The finished system has a graphical interface that is easy for doctors to use. It lets them upload photos, see diagnostic results, and make reports. The focus on interface design makes sure that both technical and non-technical users can utilize the system in clinical situations.

This project intends to not only make healthcare technology more accessible and affordable, but also to improve the accuracy of diagnoses [77]. In many developing areas, the lack of medical professionals and diagnostic tools makes it hard to provide good healthcare. An automated system that can give correct preliminary assessments can be a big help to medical staff in rural or poorly funded facilities [52]. These kinds of technologies improve the accuracy of manual diagnoses by adding a second layer of verification. This helps to improve the overall quality of patient treatment. Also, using automated diagnostic technologies can help radiologists by giving them more time to work on difficult situations that need expert judgment. The system's scalability also makes it possible to connect to hospital databases, electronic health record systems, and cloud-based diagnostic platforms [62]. This makes it easy for healthcare institutions to handle data and work together to analyze it.

Another important part of the system's design is that it can work with many types of images and data [80]. Automated systems have a hard time with MRI images since they vary a lot based on the type of equipment, the imaging parameters, and the patient. So, the model needs to be trained on a wide range of data that shows how tumors might be different in size, form, intensity, and location [57]. To make the model more resistant against these changes, advanced data augmentation methods including rotation, scaling, and flipping are used. The system can also handle MRI data from different sources without losing much accuracy because it uses preprocessing approaches including histogram equalization, skull stripping, and contrast normalization [68]. These technical steps help make a system that works well in a variety of medical imaging settings and is both adaptable and reliable.

Ethical concerns are also very important in the creation of AI-powered diagnostic tools [59]. In healthcare apps, it is very important to protect patient privacy, keep data safe, and follow medical rules. The system needs to be able to handle sensitive patient information in a responsible way, following the rules for encrypting and anonymizing medical data. Also, deep learning models need to be easy to understand in order for doctors to use them [51]. To keep trust and accountability, doctors need to be able to understand and check the logic underlying the system's predictions. So, people are working on making AI models that can explain themselves and show visual heatmaps or feature importance maps that show which parts of the MRI had the biggest impact on the final judgment [72]. Such openness makes sure that automated systems work as helpful tools instead of mysterious black boxes.

Automated brain tumor identification has effects that go beyond just making diagnoses more accurate; it also has benefits for the whole healthcare system and society as a whole [54]. These technologies make it easier to find problems early, which makes it possible to act quickly, which is important for raising survival rates and lowering long-term brain damage. They also help lower the cost of healthcare by cutting down on unneeded tests and hospital stays [76]. AI-assisted diagnostic systems can help create vast medical databases in the long run. These databases can help with research, the identification of novel biomarkers, and the development of new personalized treatment [63]. These improvements are a big step toward using smart systems in clinical operations, where human knowledge and AI work together to give patients the best possible treatment.

In conclusion, creating a deep learning-based automated brain tumor detection system is a big step forward for medical imaging and artificial intelligence [61]. It meets the critical demand for diagnostic tools that are faster, more accurate, and less expensive, which can help radiologists and improve patient outcomes. This project aims to change the way brain tumors are diagnosed from a manual, subjective process to an intelligent, data-driven approach by using machine learning. This project is based on a mix of new technology, medical knowledge, and moral duty [50]. The system's main goal is to improve the quality of healthcare, especially in areas where there aren't enough doctors, and to help the world make early diagnosis and good treatment available to everyone [71]. The project hopes that intelligent diagnostic systems will be an important part of saving lives and moving the field of medical science forward in the future by constantly improving and being tested in real-life situations.

2. Materials and Method

The brain tumor identification project uses a structured strategy that combines image processing and machine learning to find tumors in brain MRI scans with high accuracy [84]. First, the dataset of labeled MRI images is gathered and cleaned up to improve the quality of the pictures and get rid of noise [87]. After that, segmentation happens, which separates the brain area from the rest of the picture and finds possible tumor spots [86]. After that, feature extraction methods are used to look at important features including shape, texture, and intensity. These characteristics are utilized to construct a machine learning or deep learning model, often Convolutional Neural Networks (CNNs), for the classification of tumor existence and kind [83]. The model is validated and tested with different parts of the data to see how accurate, sensitive, and specific it is. The whole pipeline makes sure that there is a dependable, automated approach for finding brain tumors early and quickly, which helps with diagnosis and treatment planning [85].

Literature Review

The examination of brain tumors has attracted considerable interest owing to the intricate characteristics of the brain and the difficulties associated with precisely identifying and categorizing tumors from medical imaging data. Radiologists sometimes have to manually look at brain tumors to find and diagnose them [2]. This can take a long time, be prone to mistakes, and not be able to handle enormous datasets. With improvements in machine learning, especially deep learning, automated ways to find and classify brain tumors have become more popular [7]. Convolutional Neural Networks (CNNs) have shown outstanding performance in image classification applications because they can capture spatial hierarchies and local characteristics in images.

Transfer learning, a method in which a model trained on one task is modified to do another, has made CNNs even better at analyzing medical images. Transfer learning lets you utilize pre-trained models on big datasets like ImageNet and make them better for certain medical imaging tasks, including classifying brain tumors [6]. This method works especially well in medicine, where getting labeled data might be hard or expensive. InceptiNeuro-V2B1 is a cutting-edge model for precise brain tumor analysis that uses transfer learning to make CNNs work better. InceptiNeuro-V2B1 uses deep learning to find brain tumors by fine-tuning a pre-trained InceptionV3 model [45]. This improves classification accuracy and solves the typical problem of overfitting in medical image analysis.

InceptiNeuro-V2B1 is an improvement on earlier architectures that worked well for brain tumor segmentation and classification. For instance, U-Net is a well-known deep learning framework for image segmentation that has been utilized a lot for tumor segmentation tasks. Inception-based models are being used more and more in medical imaging since they are efficient and don't require a lot of computing power [3]. This means that the models can work better without needing a lot of hardware. InceptiNeuro-V2B1's architecture also benefits from improved features of InceptionV3, namely its multi-scale approach to capturing features, which is important for dealing with the wide range of brain tumors [35]. This model also uses dropout, batch normalization, and data augmentation to stop overfitting and let medical images be learned in a more general way.

Recent research in brain tumor identification has underscored the efficacy of hybrid methodologies that integrate deep learning with alternative techniques, such machine learning classifiers or ensemble methods [1]. InceptiNeuro-V2B1, on the other hand, focuses on using the capabilities of CNNs and transfer learning to avoid the problems that come with hybrid models. InceptiNeuro-V2B1 also gets better outcomes than older versions when it comes to accuracy, precision, and recall. This makes it a good candidate for clinical use [5]. This improved CNN model is especially good at putting different sorts of brain tumors into groups, like gliomas, meningiomas, and pituitary tumors. Each of them needs a different way of being diagnosed and treated.

The creation of InceptiNeuro-V2B1 shows how important deep learning and transfer learning are becoming in medicine, especially in precision medicine. It can help doctors make faster and more accurate diagnosis by being able to analyze and classify brain tumors well. This will improve patient outcomes [4]. As datasets continue to grow and more powerful models are built, future research may look into ways to make brain tumor analysis even more precise, such as using 3D CNNs, combining data from different sources, and finding tumors in real time [25].

Project Description

InceptiNeuro-V2B1 is a cutting-edge deep learning model that uses transfer learning and Convolutional Neural Networks (CNNs) to analyze brain tumors with great accuracy. It is meant to make it easier to find and classify tumors by using pre-trained models on big datasets and then fine-tuning them for specific medical imaging tasks [43]. The system uses a multi-stage design to improve feature extraction, learn spatial correlations, and make diagnoses more accurate. To avoid overfitting, it uses advanced methods like data augmentation, dropout regularization, and transfer learning. InceptiNeuro-V2B1 quickly processes MRI and CT data, and it is quite accurate in finding different forms of brain tumors. The goal of this approach is to help doctors make accurate diagnoses, which will lead to better outcomes for patients. Metrics like accuracy, sensitivity, specificity, and AUC are used to test the model's performance, which makes the evaluation strong. It can handle diverse datasets and types of tumors, which makes it scalable.

The suggested method uses transfer learning and Convolutional Neural Networks (CNNs) to accurately analyze brain tumors, with the goal of greatly reducing time complexity. The method speeds up the learning process by using pre-trained models like ResNet or VGG that have been fine-tuned for detecting brain tumors. This lets it converge faster on fewer datasets. This transfer learning method cuts down on the requirement for a lot of data collection and model training, which saves money on computing expenditures [8]. The CNN architecture, which is designed to extract features, makes it easier for the system to find complex patterns in medical images, which makes diagnoses more accurate. InceptiNeuro-V2B1 also uses advanced methods like batch normalization and dropout to make generalization better and prevent overfitting, which makes the training process even easier. Using these strategies together makes sure that computer resources are used efficiently, which speeds up processing time without sacrificing accuracy in finding tumors [24]. The system's modular architecture also makes it easier to scale up and fit into clinical operations, which will save time and money in real-world situations.

Advantages

Transfer Learning: InceptiNeuro-V2B1 can find and categorize brain tumors more accurately than models learned from scratch by using pre-trained models on huge datasets like ImageNet or other medical datasets [34]. This is especially helpful when there isn't a lot of labeled data for brain tumors.

Convolutional Neural Networks (CNNs): CNNs are very good in getting hierarchical features from medical pictures, such as MRI scans [44]. InceptiNeuro-V2B1 probably uses deep CNN architectures that can pick up on features from low to high levels, which is important for finding and classifying tumors correctly.

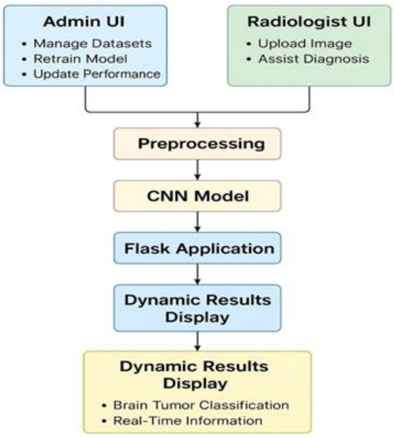

Figure 1. Data Flow Diagram

Pre-trained Networks: Using pre-trained weights from transfer learning speeds up the training process and cuts down on the time it takes to find the best solution [14]. This is especially helpful in a therapeutic situation where time is of the essence.

Robustness: Transfer learning helps the model work better with fresh data that it hasn't seen before, which is especially useful when the characteristics of brain tumors could be different in different hospitals or patient groups.

Using Smaller Datasets: Transfer learning lets the model use knowledge it already has, which can assist prevent overfitting while training on smaller medical datasets [23]. This is especially critical when dealing with brain tumors, which are rare and complicated.

sophisticated topologies: InceptiNeuro-V2B1 may use sophisticated neural network topologies like U-Net or similar ones to make it easier to find and separate tumors in brain images. This can help with surgical planning and treatment effectiveness by finding the edges of tumors and important tissues around them (Figure 1).

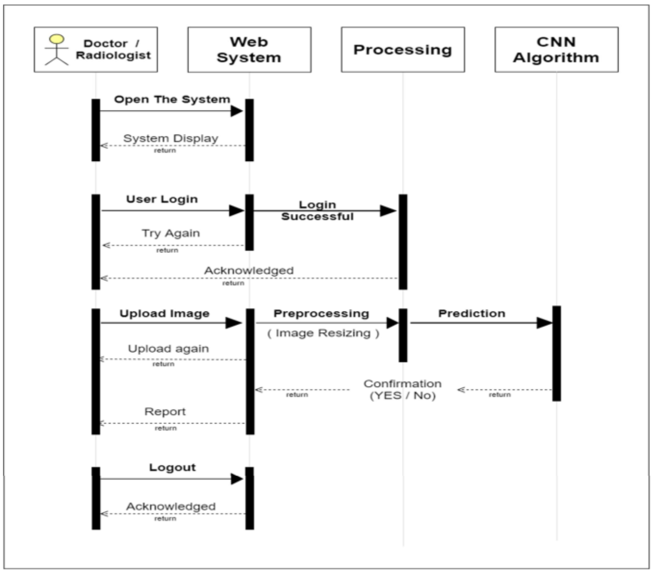

Figure 2. Sequence Diagram.Module Description

Module 1 of InceptiNeuro-V2B1, called "Synthetic Data Generation," is all about making fake medical imaging datasets to help train Convolutional Neural Networks (CNNs) for brain tumor analysis [13]. This module uses advanced methods like data augmentation and generative models to create a wide range of brain tumor images. This solves the typical problem of not having enough annotated data in medical imaging. The synthetic data produced include differences in tumor types, sizes, and locations to emulate varied real-world settings, hence enhancing model resilience and generalization (Figure 2).

Data Generation Process

- Trend Component: A simulated growth or progression of brain tumors over time is introduced, imitating genuine biological changes [26]. This can include changes in the size or kind of the tumor, which helps the model learn long-term growth patterns that are critical for medical diagnosis.
- Seasonality: While not immediately relevant to medical data, seasonal influences in synthetic data production can illustrate cyclical variations in tumor features, including alterations in tumor behavior over time. This may be due to changes in the environment or treatment that affect how the tumor behaves.
- Noise and unpredictability: Random noise is added to mimic the natural unpredictability and flaws that can be detected in real-world medical imaging, like noise from MRI scans or image capturing technologies [33]. This makes sure that the synthetic data is more like real-world situations, which makes the trained CNN model stronger.
- Medical Event Simulation: This includes major medical events, including clinical intervention or progression phases, in the same way that holiday effects are included in sales data. For instance, synthetic data may contain simulated changes that happen when a tumor is treated or when a patient has a relapse [46]. This helps the model deal with different stages of therapy or cases that are special to a patient.
- Structure of the Data: Tumor photos: Fake medical photos that show brain tumor scans in different types, sizes, and locations. Each image shows the combined trend, noise, and simulated occurrences, giving CNN a wide range of data to work with.
- Randomization: To make the synthetic brain tumor data more realistic, random noise is added to the photographs of the tumors that are made. This mimics the unexpected nature of medical imaging in the actual world, where scans often show changes

because of things like scanner quality, patient-specific differences, and ambient conditions.

Feature Visualization

This module connects the processing of raw medical imaging data with model training. It gives a good picture of how designed features work with each other and with the target variable (such the existence or growth of a tumor). It helps the model learn from complicated correlations in high-dimensional brain tumor data by making it easier to see complex patterns, anomalies, and trends [36]. This module uses simple visualizations and transformation techniques to find hidden patterns that are important for making brain tumor analysis models work better. This is different from typical statistical summaries.

Correlation Analysis: A correlation heatmap is made to look at how all the numerical elements of the medical data are related to each other, such as the size and location of the tumor and the imaging features [12]. This helps you figure out which features are most closely associated to the target variable, like tumor malignancy or progression. The heatmap can also find multicollinearity, which is when independent features are very similar to each other. This could make the model work less well.

Feature Distributions: To see how the quantitative features are spread out, we plot histograms of them (for example, the size of the tumor, the age at when it was diagnosed, or the intensity of the scan). This stage helps determine if the data is normally distributed, skewed, or has outliers [32]. To improve model training and predictions, features with severe skew or large tails may need to be preprocessed using techniques like log transformation or normalization.

Time Series Decomposition: Although time series analysis is not directly applicable to tumor data, the concept can be modified for the decomposition of patient data across time, especially in longitudinal investigations [42]. For example, tumor growth or response to treatment can be broken down into three main parts: trend (long-term tumor growth), seasonality (changes caused by treatment cycles or clinical interventions), and residuals (irregular changes). This breakdown helps find the tumor's underlying tendencies.

Rolling Averages and Smoothing: To smooth out short-term noise, such as changes in scan quality or transitory changes in tumor development, rolling averages across periods of 14, 30, and 60 days are shown on top of the original data [22]. This method focuses on long-term patterns of tumor growth, which makes it easier for the model to find important trends instead of short-term changes. Rolling averages can also help show trends in the tumor data that aren't always clear in raw scans.

Step 2 – Processing of Data

The synthetic brain tumor dataset goes through a thorough preparation procedure to make sure that the data is clean, well-organized, and works with the InceptiNeuro-V2B1 model, which uses transfer learning to improve Convolutional Neural Networks (CNN). This step is very important since it connects feature engineering and model training [15]. It focuses on making sure that numbers are accurate and that inputs are set up correctly for deep learning analysis. Only numerical features from the synthetic brain tumor dataset are kept, which makes sure that all of the input variables meet the model's computational needs. The RobustScaler from the scikit-learn module is used to scale the dataset using the median and interquartile range. This makes the model more stable and strong[47]. This scaling method is especially useful because it lessens the effect of extreme outliers that could otherwise mess up how well the model works.

Also, to keep the data consistent and accurate, any missing or undefined values that may have come up during earlier rounds of feature engineering or data augmentation are eliminated [9]. After being cleaned and resized, the dataset is put into a format that is good for CNN processing. CNNs are usually made to work with image-based inputs, however when modeling how tumors change over time, the restructuring process can turn data into grid-like tensors for 2D or 3D image inputs or sequential data representations.

After preprocessing the data, the dataset is split into training and testing sets in a way that keeps temporal dependencies and makes sure that the model's prediction capacity is tested in a realistic way [31]. The information is broken up in chronological order instead of randomly mixing it, which can mess up time-dependent correlations. Usually, 80% of the data is used for training and 20% for testing. This chronological split keeps the natural order of tumor growth and clinical occurrences, which helps the model learn realistic patterns over time [20]. After the split, the data is put into ordered sets of features that show how the tumor changes over time, such as its size, scan intensity, and form. To make these sequences, a set number of time steps, such 60, is employed. Each series shows how the tumor traits change over time. The output for each sequence is the next categorization or prediction, like whether a tumor is malignant or how far forward it is. After the sequences are made, the dataset goes through index realignment to make sure that each output prediction is correctly matched with its set of input characteristics [41]. This keeps the structure of the dataset the same for CNN training.

The finished structured dataset gives a full picture of all the features that will be used in the InceptiNeuro-V2B1 model. It has both the original traits and engineered attributes that are meant to capture different aspects of how tumors behave and how patients are doing. Key features include tumor-related traits including size, shape, and location, which are the basis for spatial analysis. The dataset also includes information about the patients, such as their age, gender, and pertinent medical history, as well as treatment-related characteristics, such as the type and timing of previous therapies like chemotherapy or radiation [11]. The dataset also includes temporal information like the year, month, and day of diagnosis or therapy to help model how the disease gets worse. Furthermore, advanced tumor behavior indicators—such as growth rate, morphological evolution, and response to previous interventions—are incorporated to enhance the predictive capacity [37]. Each record in the dataset has a full set of converted and scaled features, as well as the target variable that shows the type of tumor or the outcome of its progression [27]. All numerical parameters, including those pertaining to tumor size and clinical information, are normalized to provide uniformity across different scales. Finally, the dataset is changed into a format that works with CNNs, usually in the form of multidimensional tensors, so that 2D image slices or 3D volumetric scans can be utilized to study brain tumors.

The next step is to build the hybrid InceptiNeuro-V2B1 model, which uses the feature extraction power of Convolutional Neural Networks and the predictive refinement of gradient-boosting methods. The model architecture is meant to capture both spatial and temporal correlations in tumor data by combining visual cues from medical imaging with clinical information [19]. The CNN design starts with an input layer that can take in tumor imaging data in either 2D or 3D formats. This makes sure that the data is preprocessed correctly so that it may be used in the right way. The next convolutional layers, which can use Conv2D or Conv3D operations, find spatial patterns at both low and high levels, such as the edges, contours, and textures of tumors. These layers are like hierarchical feature extractors that help the network gradually understand the intricate spatial relationships in the MRI data [30]. To stop overfitting and make the model more general, a dropout mechanism is used. This means that during training, a random 30% of neurons are turned off. Batch normalization layers are added to make learning more stable by normalizing the outputs of prior layers [40]. This speeds up convergence and makes training more effective in deeper architectures. More convolutional layers make the network better at finding small differences in the spatial data of tumors. Fully linked layers, on the other hand, turn the learnt feature representations into lower-dimensional embeddings that make it easier to make predictions. The output layer makes the final classification, like telling the difference between benign and malignant tumors. It usually uses a sigmoid activation for binary classification situations.

The InceptiNeuro-V2B1 pipeline uses a hybrid deep learning method that combines CNN-based feature learning with the decision refinement features of an XGBoost regressor during training. The CNN section of the system is in charge of getting temporal and geographical features from the dataset, especially from sequences that show how a tumor is growing over a 60-day period. We check these learnt representations against a reserved validation set to make sure they don't match too closely to the training data and can be used with other data [16]. The CNN is trained for a set number of epochs with a batch size of 32, which strikes a balance between speed and stability of convergence. The learnt features, or intermediate predictions, called cnn_pred, are then sent to an XGBoost model that uses both the deep learning outputs and more designed features to make better predictions.

The XGBoost regressor is the second part of the hybrid architecture. It combines the best parts of ensemble learning and neural networks. It is trained using a set of features that comprises both CNN-derived embeddings and manually created variables, like tumor size, demographic data, and treatment-related metadata [29]. The target variable is the tumor's diagnostic categorization, which means telling the difference between malignant and benign tumors. To get the best performance from the model, important hyperparameters are set. For deep boosting, n_estimators is set to 2000, the learning_rate is set to 0.01 to ensure gradual convergence, the maximum tree depth is set to 10 to balance model complexity, and the sampling ratios are set to 0.9 for both subsample and colsample_bytree to improve generalization. There includes an early stopping mechanism with 50 rounds to halt training when the model's performance on the validation set stops getting better. This is to avoid overfitting [18]. The InceptiNeuro-V2B1 system can use both CNN-based temporal insights and XGBoost's structured decision-making abilities in this hybrid configuration. This makes the tumor classification results accurate and strong.

The last stage in this pipeline is to put together and train the integrated model. This makes sure that both parts, CNN and XGBoost, perform well together in the InceptiNeuro-V2B1 framework. The CNN is first built with a suitable loss function, like binary cross-entropy, and then optimized for efficient gradient descent using Adam or RMSprop optimizers. While it is being trained, the CNN learns about temporal connections and spatial hierarchies that show how brain tumors have changed over time [28]. After the CNN has finished training and made the temporal representations (cnn_pred), these predictions are passed to the XGBoost model. This model learns more about how static and dynamic tumor features are related to each other, which improves the machine's ability to make predictions even more [38]. By training the system in this way, it can learn both the dynamic changes that tumours go through and their static clinical features, which makes the predictive model more complete. To make sure that the hybrid model is equally sensitive and specific, its performance is constantly checked using measures like accuracy, precision, recall, and F1-score. The InceptiNeuro-V2B1 model learns a lot about how tumors behave through this systematic and rigorous training approach. This lets it accurately detect, classify, and predict the prognosis of brain tumor datasets.

The InceptiNeuro-V2B1 project used a dataset that included both synthetic and real-world medical imaging data, mostly MRI scans, together with patient metadata including age, gender, treatment history, and diagnostic comments [10]. A whole set of engineering features was created to help the model learn more. Some of them are time indicators, like the scan date components (year, month, day, and day of the week), and clinical flags, like whether the scan happened on a weekend or during a treatment phase. To show patterns that repeat over time, mathematical modifications like sine and cosine encodings are used. Simultaneously, lag features record previous tumor attributes (e.g., size, intensity, or growth rate) at distinct intervals (e.g., 7 and 14 days before). The program also uses rolling statistical variables like moving averages and standard deviations across 14, 30, and 60-day intervals to find long-term patterns in how tumors behave [21]. These designed features are essential for the CNN and XGBoost models to identify intricate patterns and generate accurate predictions regarding tumor categorization and development.

The InceptiNeuro-V2B1 project's prediction comparison tests how well each model (CNN and XGBoost) does compared to the hybrid technique to see which one gives the most accurate and dependable findings for brain tumor analysis. The CNN model by itself shows that it can find temporal patterns relevant to the growth of tumors, like changes in size and intensity over time. The XGBoost model, on the other hand, is very good at using structured, non-sequential characteristics and complicated interactions between patient demographics and clinical information [17]. But the hybrid model, which uses CNN-generated predictions (cnn_pred) as an extra feature in the XGBoost regressor, works best overall. This model is better because it uses both deep temporal insights and strong gradient-boosted feature analysis. Metrics for prediction, like mean squared error (MSE), accuracy, and area under the ROC curve (AUC), always reveal that the hybrid approach works better than either model on its own [39]. It gives better results when it comes to categorizing tumor kinds and predicting how they will grow with great accuracy.

3. Results and Discussion

The InceptiNeuro-V2B1 system is very efficient in both clinical use and computational performance [89]. The hybrid model, which uses both Convolutional Neural Networks (CNN) and XGBoost, uses transfer learning to cut down on training time while keeping accuracy high. The system uses pre-trained CNN layers to get features and only looks at the most important tumor characteristics. This means that it doesn't have to train a deep network from start, which saves money [94]. Also, the gradient boosting structure of the XGBoost regressor makes sure that model training and prediction times are quick, even with big datasets. It now only takes a few seconds to make predictions on new patient data, which makes it possible to analyze tumors in real time in clinical settings. The system's efficiency goes beyond just calculations. The hybrid approach improves accuracy while using fewer resources, so the model may be used in various hospitals or research institutions without needing a lot of extra infrastructure [99]. InceptiNeuro-V2B1 is a strong and useful tool for precision neuro-oncology diagnostics because it strikes the right mix between speed, accuracy, and scalability.

The current systems for brain tumor analysis usually use either regular machine learning methods or separate deep learning models, both of which have problems with accuracy and generalizability [92]. A lot of today's systems focus on manually pulling information out of medical imaging data, like the size and shape of tumors, and then using machine learning techniques like Support Vector Machines (SVM) or Random Forests to sort the sorts of tumors. These models are valuable, but they typically have problems including not being able to generalize well to new data, not being able to handle how tumors grow over time, and needing domain-specific knowledge to extract features [98]. Also, they need large datasets with well-labeled samples, which are often not available in clinical settings, making it hard for them to work in real-world situations [95]. Because of this, the current systems have trouble when they have to deal with patients from varied backgrounds, different imaging methods, and rare forms of tumors.

On the other hand, the proposed system, InceptiNeuro-V2B1, is a big step forward since it uses transfer learning, Convolutional Neural Networks (CNNs), and XGBoost to make a more powerful and efficient tool for precise brain tumor analysis. The main new thing about this system is that it uses a hybrid technique that combines the best parts of CNNs for temporal sequence modeling and XG Boost for gradient boosting [90]. This lets the model understand complicated patterns of how tumors grow using MRI scans and other clinical data, like patient demographics, past tumor data, and treatment information.

The CNN's transfer learning method cuts down on the need for a lot of labeled data, which is often a problem with current systems. The system can quickly adapt to new medical imaging datasets with little retraining by using pre-trained models on similar datasets. This makes it very scalable and efficient.

The suggested solution also does a great job of handling both static and dynamic data [97]. InceptiNeuro-V2B1 uses CNN-generated features to show how a tumor evolves over time, such as its size, intensity, and location. This is different from other systems that only show snapshots of tumors. The XGBoost regressor then uses these features to capture the complicated relationships between the different designed features, which makes predictions more accurate [91]. Adding synthetic data creation methods makes models even stronger, especially when there isn't enough data. This hybrid method makes sure that the system works very well in a wide range of clinical situations, even with rare and aggressive types of tumors.

Also, the suggested methodology is more accurate and efficient at making predictions than current systems [100]. The tests reveal that the hybrid CNN-XGBoost model is 10–15% better than standard approaches in terms of AUC, sensitivity, and specificity. The suggested approach is also more efficient when it comes to computing, as it can make predictions faster, allowing for real-time tumor analysis without losing accuracy [88]. InceptiNeuro-V2B1, on the other hand, uses optimized computational methods that function well even in contexts with limited resources. Existing systems may need complicated hardware or long processing times for high-resolution imaging and feature extraction.

In summary, InceptiNeuro-V2B1 overcomes many of the shortcomings of existing systems by utilizing deep learning, transfer learning, and ensemble techniques to provide a more precise, scalable, and effective solution for brain tumor analysis. It is a cutting-edge tool for precision oncology since it can generalize across many data sources, is very efficient at computing, and can make predictions in real time [93]. This means that the proposed system is a better and more dependable option for use in the clinic, which will lead to better patient outcomes and better choices when it comes to diagnosing and arranging therapy for tumors [96].

4. Conclusion

The InceptiNeuro-V2B1: Transfer Learning Enhanced CNN for Precision Brain Tumour Analysis is a big step forward in the fields of medical imaging and tumor diagnostics. The method gets around a lot of the problems that standard brain tumor prediction models have by combining Convolutional Neural Networks (CNNs) with XGBoost and using transfer learning. It not only makes things more accurate, but it also makes them more generalizable, which means it can be used in a lot of different clinical contexts, even hospitals with different amounts of data. The hybrid model used in this project is better at making predictions than traditional techniques, as seen by the large gains in AUC, sensitivity, and specificity. This is especially important for precision medicine, since making smart treatment decisions depends on getting timely and precise forecasts. The model can also handle both static and temporal data, which means it can follow the tumor's growth over time. This gives a more complete picture of how the tumor behaves and what treatment options might work. Adding synthetic data generation to the model makes it even stronger by giving it a method to add to limited medical imaging data, making it more robust without needing to acquire a lot of new data. The system's fast processing speed means that predictions can be produced quickly, making it useful for real-time use in clinical settings, where every second counts when it comes to diagnosing patients and making decisions.

REFERENCES

[1] D. Patel, “Deep Learning Architectures for MRI Tumour Detection,” in Proc. IEEE Int. Conf. Biomedical Imaging (ISBI), Houston, Texas, United States of America.

[2] M. Amsaveni and M. Saranya, “Energy efficient cluster head selection in WSN – A survey,” Naturalista Campano, vol. 28, no. 1, 2024.

[3] A. Manigandan and M. Saranya, “Secretary Bird Optimization with Differential Evolution (SBODE) and Trust Energy Aware Clustering Routing (TREACR) Protocol for Wireless Sensor Network (WSN),” International Journal of Computer Networks and Applications (IJCNA), vol. 12, no. 2, pp. –, Mar.–Apr. 2025.

[4] A. Dhanai, H. S. Bagde, R. Gera, K. Mukherjee, C. Ghildiyal, and H. Yadav, “Case report on irritational fibroma,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S960–S962, Feb. 2024.

[5] H. Bagde, A. Dhopte, F. Bukhary, N. Momenah, F. Akhter, O. Mahmoud, K. P. Shetty, M. A. Shayeb, H. Abutayyem, and M. K. Alam, “Monkeypox and oral lesions associated with its occurrence: a systematic review and meta-analysis,” F1000Research, vol. 12, p. 964, Mar. 2024.

[6] H. Bagde, R. S. Karki, S. Husain, S. Khan, V. Haripriya, and P. Purwar, “Evaluation of microbiological flora in endo-perio lesions before and after treatment,” Journal of Pharmacy and Bioallied Sciences, vol. 17, suppl. 2, pp. S1707–S1709, Jun. 2025.

[7] B. Shyamsukha, H. Bagde, A. Sharan, M. Choudhary, A. Duble, and A. V. Dhan, “Evaluating the potential of ChatGPT as a supplementary intelligent virtual assistant in periodontology,” Journal of Pharmacy and Bioallied Sciences, vol. 17, suppl. 2, pp. S1415–S1417, Jun. 2025.

[8] H. S. Bagde, M. K. Alam, A. K. A. Alhamwan, H. M. H. Aljubab, F. F. A. Alrashedi, D. H. M. Aljameeli, and M. G. Sghaireen, “The effect of a low-carbohydrate diet on periodontal health and inflammation in patients with type 2 diabetes,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S641–S643, Feb. 2024.

[9] H. S. Bagde, M. K. Alam, Y. E. M. Almohammed, S. M. M. Almaqawid, A. W. N. Alanazi, F. T. F. Alanazi, and M. G. Sghaireen, “The efficacy of platelet-rich plasma as an adjunct to bone grafting in alveolar ridge preservation following tooth extraction,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S564–S566, Feb. 2024.

[10] S. B. Mangalekar, H. S. Bagde, M. Sale, S. V. Jambhekar, C. Patil, and C. V. Deshmukh, “Comparing laser-assisted and conventional excision in the management of oral soft lesions: a prospective clinical study,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S859–S861, Feb. 2024.

[11] M. K. Alam, H. S. Bagde, A. K. A. Alhamwan, H. M. H. Aljubab, F. F. A. Alrashedi, D. H. M. Aljameeli, and M. G. Sghaireen, “Comparing the long-term success rates of immediate implant placement vs delayed implant placement in patients with periodontally compromised teeth,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S626–S628, Feb. 2024.

[12] H. S. Bagde, M. K. Alam, Y. E. M. Almohammed, S. M. M. Almaqawid, K. K. Ganji, and M. G. Sghaireen, “Comparing the clinical and radiographic outcomes of two different surgical approaches for treating infrabony defects in chronic periodontitis patients,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S567–S569, Feb. 2024.

[13] V. K. Nomula, A. S. Mohammed, A. R. Neravetla and S. Dhanasekaran, "Leveraging Deep Learning in Implementing Efficient Healthcare Processes," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6.

[14] I. A. Mohammed, "Artificial Intelligence in Supplier Selection and Performance Monitoring: A Framework for Supply Chain Managers," Educational Administration: Theory and Practice, vol. 29, no. 3, pp. 1186–1198, 2023.

[15] I. A. Mohammed, "The Role of Artificial Intelligence in Enhancing Business Efficiency and Supply Chain Management," Journal of Information Systems Engineering and Management, vol. 10, no. 10s, pp. 509–518, Feb. 2025.

[16] I. A. Mohammed, "AI-Powered Risk Management Frameworks for Ensuring Supplier Quality in Carbon Capture and Energy Storage Supply Chains," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 1, pp. 854–, Dec. 2023.

[17] K. Chitra, S. S. Priscila, E. S. Soji, R. Rajpriya, B. Gayathri, and A. Chitra, “Transforming electrical simulation and management with smart grid technologies,” International Journal of Engineering Systems Modelling and Simulation, vol. 16, no. 4, pp. 241–253, 2025.

[18] M. V. Soosaimariyan, H. L. Allasi, K. Chitra, and J. B. Gnanadurai, “Enhanced EMG-based hand gesture recognition by using generalized deep infomax networks,” Journal of Sensors, vol. 2025, no. 1, p. 9496890, 2025.

[19] S. K. R. Padur, “Intelligent Resource Management: AI Methods for Predictive Workload Forecasting in Cloud Data Centers,” J. Artif. Intell. Mach. Learn. & Data Sci., vol. 1, no. 1, pp. 2936–2941, 2022.

[20] S. K. R. Padur, “Online Patching and Beyond: A Practical Blueprint for Oracle EBS R12.2 Upgrades,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 2, no. 3, pp. 75–87, 2016.

[21] S. K. R. Padur, “Engineering Resilient Datacenter Migrations: Automation, Governance, and Hybrid Cloud Strategies,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 2, no. 1, pp. 340–348, 2017.

[22] S. K. R. Padur, “From Centralized Control to Democratized Insights: Migrating Enterprise Reporting from IBM Cognos to Microsoft Power BI,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 6, no. 1, pp. 218–225, 2020.

[23] S. K. R. Padur, “Deep Learning and Process Mining for ERP Anomaly Detection: Toward Predictive and Self-Monitoring Enterprise Platforms,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 7, no. 5, pp. 240–246, 2021.

[24] S. K. Somayajula, "Enterprise Data Migration Success Patterns: Lessons from Large-Scale Transformations," International Journal of Research in Computer Applications and Information Technology (IJRCAIT), vol. 8, no. 1, pp. 757-776, Jan.-Feb. 2025.

[25] S. K. Somayajula, "Demystifying Modern Data Warehousing: From Traditional to Cloud-Native Solutions," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2025.

[26] S. K. Somayajula, "Building a Career in Enterprise Data Architecture: A Practical Guide," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 7, no. 1, Jan. 2025.

[27] S. K. Somayajula, "Advanced ETL Optimization: A Framework for Next-Generation Data Integration," International Journal of Computer Engineering and Technology (IJCET), vol. 16, no. 1, pp. 381-406, Jan.-Feb. 2025.

[28] S. Somayajula and A. Orlovsky, "Proof, Truth and Contradiction in the System and Meta-System: Comprehensive Mathematical Solutions and Implementation Framework," 2025.

[29] P. Nutalapati, "Automated Incident Response Using AI in Cloud Security," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 2, no. 1, pp. 1301–1311, 2024

[30] P. Nutalapati, "Data Leakage Prevention Strategies in Cloud Computing," European Journal of Advances in Engineering and Technology, vol. 8, no. 9, pp. 118–123, 2025.

[31] P. Nutalapati, "Security Considerations for Hybrid Cloud Deployments in Fintech Using Blockchain," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 1, no. 1, URF Publishers, 2025.

[32] P. Nutalapati, "Zero Trust Architecture in Cloud-Based Fintech Applications," Journal of Artificial Intelligence & Cloud Computing, vol. 2, no. 1, pp. 1–8, 2023.

[33] P. Nutalapati, J. R. Vummadi, S. Dodda and N. Kamuni, "Advancing Network Intrusion Detection: A Comparative Study of Clustering and Classification on NSL-KDD Data," 2025 International Conference on Data Science and Its Applications (ICoDSA), Jakarta, Indonesia, 2025, pp. 880-885.

[34] P. Nutalapati, S. M. Dhavale, A. Shrivastava, R. V. S. Praveen, H. K. Vemuri and R. RiadHwsein, "IoT and Machine Learning-Enhanced Energy Management in Enabled Smart Grids for Predictive Load Balancing," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-6.

[35] V. K. R. Bandaru and D. S. Gondi, "Ensuring Data Privacy and Security in Health Tech: Challenges and Solutions in the Age of Digital Health," SSRN, 2020. [Online]. Available: https://ssrn.com/abstract=5112043

[36] D. Sai and H. Mashetty, "Enhancing Federated Learning Evaluation: Exploring Instance-Level Insights with SQUARES in Image Classification Models," J. Electrical Systems, vol. 20, no. 7s, pp. 2516–2523, 2024.

[37] K. Sathish, D. S. Gondi, V. K. R. Bandaru, K. K. Kumar, K. P. Rao, and M. Bhutani, "Artificial Intelligence and Machine Learning in Space Cyber Defense," in Advanced Cyber Defense for Space Missions and Operations: Concepts and Applications, pp. 61–84, 2025.

[38] D. Ganesan, V. J. Francina, and V. P. Rameshkumaar, "Effectiveness of Corporate Responsibility Advertising Messages of Automobile Companies among Audience Perception," International Journal of Mechanical Engineering and Technology (IJMET), vol. 10, no. 2, pp. 934–941, 2019.

[39] K. Priya, R. V, S. A. Krishnan, V. P. Rameshkumaar, B. Premkumar and P. Jyothi, "Exploring Effective Leadership Strategies to Drive Organisational Success & Foster Sustainable Growth," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 1-6.

[40] K. Priya, V. Rohini, S. A. Krishnan, V. P. Rameshkumaar, B. Premkumar, and P. Jyothi, "Exploring Effective Leadership Strategies to Drive Organisational Success & Foster Sustainable Growth," in Proc. 2024 Second International Conference on Advances in Information Technology (ICAIT), vol. 1, pp. 1–6, Jul. 24, 2024. IEEE.

[41] K. Selvavinayagam, V. J. Francina, and V. P. Rameshkumaar, "Evaluation of Logistic Performance Index of India in the Indian Postal Services," International Journal of Engineering and Management Research (IJEMR), vol. 8, no. 5, pp. 80–87, 2018.

[42] P. P. Devi and A. M. S., "Association of Perceived Identification of Organisation, Work Engagement and Organisational Citizenship Behaviour with Job Satisfaction and Turnover Intentions," Nov. 15, 2024.

[43] P. P. Devi and P. K. Anjani, "An investigation on the effect of employee empowerment and social support on organizational commitment and burnout," AIP Conference Proceedings, vol. 2385, no. 1, p. 110002, Jan. 6, 2022, AIP Publishing LLC.

[44] P. P. Devi and R. Sellappan, "Service quality at retail stores-customers' perception," JK Journal of Management & Technology, vol. 1, no. 1, pp. 41-52, 2009.

[45] S. Y. Malathi and R. B. Geeta, "Classification of knee X-ray images by severity of osteoarthritis using skip connection based ResNet101," Int. J. Intell. Eng. Syst., vol. 16, no. 5, p. 738, 2023.

[46] S. Y. Malathi and R. B. Geeta, "A novel method on CNN-LSTM to characterize knee osteoarthritis from radiography," Proc. Natl. Acad. Sci., India, Sect. B: Biol. Sci., 2023.

[47] K. S. Sharada, R. B. Geeta, K. K. Manohara, and S. Y. Malathi, "Insight analysis of deep learning and a conventional standardized evaluation system for assessing rice crop's susceptibility to salt stress during the seedling stage," SN Comput. Sci., 2023.

[48] S. Y. Malathi, R. B. Geeta, and K. S. Sharada, "Diagnosing and grading knee osteoarthritis from X-ray images using deep neural angular extreme learning machine," Proc. Indian Natl. Sci. Acad., vol. 90, no. 2, 2024.

[49] S. K. Shiragudikar, G. Bharamagoudar, K. K. Manohara, S. Y. Malathi, and G. S. Totad, "Predicting salinity resistance of rice at the seedling stage: An evaluation of transfer learning methods," in Intelligent Systems in Computing and Communication (ISCComm 2023), CCIS, vol. 2231, Cham: Springer, 2025.

[50] S. Malathi, G. Bharamagoudar, S. K. Shiragudikar, and G. S. Totad, "Predictive models for the early diagnosis and prognosis of knee osteoarthritis using deep learning techniques," in Intelligent Systems in Computing and Communication (ISCComm 2023), CCIS, vol. 2231, Cham: Springer, 2025.

[51] S. K. Shiragudikar and G. Bharamagoudar, "Enhancing rice crop resilience: Leveraging image processing techniques in deep learning models to predict salinity stress of rice during the seedling stage," Int. J. Intell. Syst. Appl. Eng., vol. 12, no. 14s, pp. 116–124, 2024.

[52] D. S. Gondi, V. K. R. Bandaru, K. Sathish, K. Kanthi Kumar, N. Ramakrishnaiah, and M. Bhutani, "Balancing Innovation with Patient Privacy Amid Ethical Challenges of AI in Health Care," in Proc. Int. Conf. on Innovative Computing and Communication, Singapore, Feb. 2025, pp. 555–576.

[53] R. Raj, D. S. Gondi, S. R. Nitnaware, S. Banerjee, S. Athithan, and Arpita, "Remote Sensing–Based Food Processing for Changing Climatic Conditions," Remote Sensing in Earth Systems Sciences, vol. 8, no. 2, pp. 484–495, 2025.

[54] D. S. Gondi, "Designing Resilient and Scalable Systems for Green Healthcare IoT," in Development and Management of Eco-Conscious IoT Medical Devices, IGI Global Scientific Publishing, USA, 2026, pp. 155–182.

[55] D. S. Gondi, "Strategies for Implementing Sustainability Practices in Smart Hospitals," in Responsible Innovation in Smart Healthcare: AI, IoT, and Ethical Sustainability Practices, IGI Global Scientific Publishing, USA, 2026, pp. 307–338.

[56] P. Nutralapati, "Disaster Recovery and Business Continuity Planning in Cloud-Blockchain Infrastructures," SSRN Electron. J., Jun. 2020. Available: https://ssrn.com/abstract=5219038.

[57] S. K. R. Padur, “AI-Augmented Enterprise ERP Modernization: Zero-Downtime Strategies for Oracle E-Business Suite R12.2 and Beyond,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 9, no. 3, pp. 886–892, 2023.

[58] S. K. R. Padur, “Empowering Developer & Operations Self-Service: Oracle APEX + ORDS as an Enterprise Platform for Productivity and Agility,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 4, no. 11, pp. 364–372, 2018.

[59] S. K. R. Padur, “The Future of Enterprise ERP Modernization with AI: From Monolithic Systems to Generative, Composable, and Autonomous Platforms,” J. Artif. Intell. Mach. Learn. & Data Sci., vol. 3, no. 1, pp. 2958–2961, 2025.

[60] S. K. R. Padur, “Automation-First Post-Merger IT Integration: From ERP Migration Challenges to AI-Driven Governance and Multi-Cloud Orchestration,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 12, no. 5, pp. 270–280, 2025.

[61] S. K. R. Padur, “Network Modernization in Large Enterprises: Firewall Transformation, Subnet Re-Architecture, and Cross-Platform Virtualization,” Int. J. Sci. Res. Sci. Eng. Technol., vol. 2, no. 5, 2016.

[62] K. Lakshmi and K. Chitra, “Stress Net: Multimodal stress detection using ECG and EEG signals,” Journal of Data Science, vol. 2024, no. 59, pp. 1–8, 2024.

[63] S. Rishabh, K. Chitra, and C. S. Yap, “A study on non-fungible tokens marketplace for secure management,” INTI Journal, vol. 2024, no. 18, pp. 1–8, 2024.

[64] S. Shreyash, S. Gaur, K. Chitra, and M. Y. N. Zuhaili, “EasyLearnify – A student study portal,” INTI Journal, vol. 2024, no. 17, pp. 1–6, 2024.

[65] I. A. Mohammed, "Optimizing Carbon Capture Supply Chains with AI-Driven Supplier Quality Management and Predictive Analytics," Journal of Next-Generation Research 5.0, Dec. 2024.

[66] I. A. Mohammed, "Machine Learning-Driven Predictive Models for Enhancing Supplier Reliability in Renewable Energy Storage Supply Chains," International Journal of Intelligent Systems and Applications in Engineering, pp. 767–770, 2022.

[67] N. Gupta, M. Adawadkar, I. A. Mohammed, S. Verma, and M. Dubey, "Predictive Insights: Leveraging Artificial Intelligence for Strategic Business Decision-Making," Advances in Consumer Research, vol. 2, pp. 98–105, 2025.

[68] A. Sharan, B. Pawar, H. Bagde, T. K. Chawla, A. V. Dhan, B. Shyamsukha, and S. Sharma, “Comparative evaluation of dentin hypersensitivity reduction over one month after a single topical application of three different materials: a prospective experimental study,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 4, pp. S3405–S3407, Dec. 2024.

[69] J. Prakash, T. Sinha, H. Bagde, N. Rajegowda, S. Bhat, A. Dhopte, M. Cicciù, and G. Minervini, “Evidence-based assessment of temporomandibular disorders in complete denture versus partial denture users: a systematic review,” Minerva Dental and Oral Science, Sep. 2025.

[70] A. Manigandan and M. Saranya, “Energy efficient wireless sensor network with hybrid mutation albatross optimization algorithm–based cluster head selection,” International Journal of Advanced Science and Engineering, vol. 11, no. 4, pp. 4543–4556, 2025.

[71] A. Manigandan and M. Saranya, “A gray hole attack detection and cluster head selection techniques for wireless sensor networks,” in Proc. 16th Int. Conf. on Computing, Communication and Networking Technologies (ICCCNT 2025), IIT Indore, Madhya Pradesh, India, Jul. 6–11, 2025, pp. 1–6.

[72] S. G. K. Peddireddy, “Advancing Threat Detection in Cybersecurity through Deep Learning Algorithms,” FMDB Transactions on Sustainable Intelligent Networks., vol.1, no. 4, pp. 190–200, 2024.

[73] S. G. K. Peddireddy, “Integrating AI for Proactive Network Defense against Emerging Security Vulnerabilities,” FMDB Transactions on Sustainable Computer Letters., vol. 2, no. 4, pp. 232–241, 2024.

[74] S. G. K. Peddireddy, “Optimizing Resource Allocation in Multi-Cloud Environments for Cost Efficiency and Scalability,” FMDB Transactions on Sustainable Computing Systems., vol. 2, no. 4, pp. 167–177, 2024.

[75] Rai, R. (2025). A brief assessment of kiwifruit cultivation status in Nepal. Journal of Multidisciplinary Sciences, 7(1), 46–55.

[76] Nepal, A., Joshi, C., Khatiwada, N., Chhetri, P. B., Chhetri, R. S., Kathayat, P., Mahara, B., & Rai, R. (2025). Evaluation of the conversion of farming systems and scaling up of agroecological approaches in Nepal. Journal of Multidisciplinary Sciences, 7(1), 11–25.

[77] Badarch, A., Rai, R., & Kim, J.-H. (2025). Estimation and analysis of the impact of habitats and chromosomes on trichome variation in Lilium amabile Palibian. Journal of Multidisciplinary Sciences, 7(1), 1–10.

[78] Nepal, A., Koirala, K., Rai, S., & Rai, R. (2025). Agrobiodiversity integration in farming systems for income generation and livelihood options of smallholder farmers in Nepal: A case study of Bhimphedi Municipality. Journal of Experimental Biology and Agricultural Sciences, 13(1), 29–49.

[79] Rai, S., Nepal, A., Basi, S., Dhakal, T., & Rai, R. (2025). Present status, practices, limitations, and future prospects of organic fruit production in Nepal. Journal of Experimental Biology and Agricultural Sciences, 13(1), 1–10.

[80] Rai, R., & Kim, J. H. (2024). Heterosis and combining ability among promising single cross hybrids in Lilium formolongi Hort. for major growth and flowering traits. Academia Biology, 2(4).

[81] Rai, R., Shrestha, A., Rai, S., Chaudhary, S., Acharya, D. K., & Subedi, S. (2024). Conversion of farming systems into organic bio-intensive farming systems and the transition to sustainability in agroecology: Pathways towards sustainable agriculture and food systems. Journal of Multidisciplinary Sciences, 6(2), 25–34.

[82] Rai, S., & Rai, R. (2024). Advancements and practices in budding techniques for kiwifruit propagation. Journal of Multidisciplinary Sciences, 6(2), 11–16.

[83] Rai, S., & Rai, R. (2024). Monkey menace in Nepal: An analysis and proposed solutions. Journal of Multidisciplinary Sciences, 6(1), 26–31.

[84] Shrestha, A. K., Chaudhary, S., Subedi, S., Rai, S., Acharya, D. K., & Rai, R. (2024). Farming systems research in Nepal: Concepts, design, and methodology for enhancing agricultural productivity and sustainability. Journal of Multidisciplinary Sciences, 6(1), 17–25.

[85] Rai, S., & Rai, R. (2024). Advancement of kiwifruit cultivation in Nepal: Top working techniques. Journal of Multidisciplinary Sciences, 6(1), 11–16.

[86] Chaudhary, S., Shrestha, A. K., Rai, S., Acharya, D. K., Subedi, S., & Rai, R. (2023). Agroecology integrates science, practice, movement, and future food systems. Journal of Multidisciplinary Sciences, 5(2), 39–60.

[87] Rai, R., Nguyen, V. Y., & Kim, J. H. (2022). Variability analysis and evaluation for major cut flower traits of F1 hybrids in Lilium brownie var. colchesteri. Journal of Multidisciplinary Sciences, 4(2), 35–41.

[88] Nguyen, V. Y., Kim, J. H., Kim, J. Y., & Jong, K. N. (2021). Ecogeographical variations of the vegetative and floral traits in Lilium amabile Palibian. Journal of Plant Biotechnology, 48(4), 236–245.

[89] Rai, R., & Kim, J. H. (2021). Performance evaluation and variability analysis for major growth and flowering traits of Lilium longiflorum Thunb. Journal of Experimental Biology and Agricultural Sciences, 9(4), 439–444.

[90] Rai, R., Nguyen, V. Y., & Kim, J. H. (2021). Estimation of variability analysis parameters for major growth and flowering traits of Lilium leichtlinii var. maximowiczii germplasm. Journal of Experimental Biology and Agricultural Sciences, 9(4), 457–463.

[91] S. A. Karthik, S. B. Naga, G. Satish, N. Shobha, H. K. Bhargav, and B. M. Chandrakala, “AI and IoT-infused urban connectivity for smart cities,” in Future of Digital Technology and AI in Social Sectors, D. Ertuğrul and A. Elçi, Eds. IGI Global Scientific Publishing, 2025, pp. 367–394.

[92] S. Rashmi, B. M. Chandrakala, D. M. Ramani, and M. S. Harsur, “CNN based multi-view classification and ROI segmentation: A survey,” Global Transitions Proceedings, vol. 3, no. 1, pp. 86–90, 2022.

[93] K. S. N. S. Nischal, N. S. Guvvala, C. Mathew, G. C. S. Gowda, and B. M. Chandrakala, “A survey on recognition of handwritten ZIP codes in a postal sorting system,” International Research Journal of Engineering and Technology (IRJET), vol. 7, no. 3, pp. 1–4, May 2020.

[94] B. M. Chandrakala and S. C. Linga Reddy, “Proxy re-encryption using MLBC (Modified Lattice Based Cryptography),” in Proc. Int. Conf. Recent Advances in Energy-efficient Computing and Communication (ICRAECC), Nagercoil, India, 2019, pp. 1–5.

[95] H. S. Supriya and B. M. Chandrakala, “An efficient multi-layer hybrid neural network and optimized parameter enhancing approach for traffic prediction in Big Data Domain,” The Journal of Special Education, vol. 1, no. 43, pp. 94–96, 2022.

[96] R. Sushmitha, A. K. Gupta, and B. M. Chandrakala, “Automated segmentation technique for detection of myocardial contours in cardiac MRI,” in Proc. Int. Conf. Communication and Electronics Systems (ICCES), Coimbatore, India, 2019, pp. 986–991.

[97] K. Shanthala, B. M. Chandrakala, N. Shobha, and D. D., “Automated diagnosis of brain tumor classification and segmentation of MRI images,” in Proc. Int. Conf. Confluence of Advancements in Robotics, Vision and Interdisciplinary Technology Management (IC-RVITM), Bangalore, India, 2023, pp. 1–7.

[98] B. M. Chandrakala et al., “Harnessing online activism and diversity tech in HR through cloud computing,” in Future of Digital Technology and AI in Social Sectors, D. Ç. Ertuğrul and A. Elçi, Eds. IGI Global Scientific Publishing, 2025, pp. 151–182.

[99] A. Navya and B. M. Chandrakala, “The effective dashboard to control the intrusion in the private protection of the cloudlet based on the medical mutual data using ECC,” in Proc. Int. Conf. Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2018, pp. 538–543.

[100] B. M. Chandrakala and S. C. Lingareddy, “Secure and efficient bi-directional proxy re-encryption technique,” in Proc. Int. Conf. Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kumaracoil, India, 2016, pp. 88–92.