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BrainCL: Brain Tumor Diagnosis Using Hybrid Deep Learning and Machine Learning Techniques

Nusrat Jahan Trisna, Saikat Baul, Md. Khairul Alam Mazumder, Md. Ariful Islam and Farzana Bente Alam
Department of Computer Science
American International University-Bangladesh
Dhaka, Bangladesh
nusrat.trisna@aiub.edu, saikatbaul@aiub.edu, khairul@aiub.edu, ariful@aiub.edu, farzana.alam@aiub.edu

Abstract

Magnetic Resonance Imaging (MRI) is an important diagnostic tool for the diagnosis of brain tumors but is limited when achieving accurate classification and segmentation, especially with small sized or irregularly outlined tumors. To overcome these shortcomings, this study puts forward a hybrid model combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks with the objective of achieving maximum classification accuracy while maintaining minimal model simplicity. The suggested approach is compared with individual CNN, Random Forest (RF), Extreme Learning Machine (ELM), and LSTM models for comparison of performance. Experimental results demonstrate that the hybrid CNN–LSTM model outperforms the comparative approaches, with accuracy being 94.50%, precision being 94.55%, and recall being 94.51%. Moreover, the model provides strong ROC-AUC performance, good tumor localization, and real-time applicability. With a balance in terms of accuracy and computation efficiency, the proposed framework offers a strong diagnostic tool to support radiologists in the timely detection, improve treatment planning, and in turn, patient outcomes.

Keywords
Brain tumor, Neural network methods, MRI image, CNN, ELM, LSTM.

1. Introduction
A brain tumor is an abnormal growth of tissue that happens when cells grow too rapidly and disturb the brain's normal mechanisms for keeping things in order (Kuluchi, 2021). Even small abnormal growths are frightening concerns since the skull is hard and encloses the brain. Both benign and malignant tumors raise intracranial pressure, which greatly raises the risk of neurological injury or death (Kuluchi, 2021). There are two main types of brain tumors: primary tumors that arise in the brain, and metastatic tumors (Peddi, 2016), which invade the brain from other locations in the body, including lungs or breasts. To date, scientists have named more than 150 unique types of brain tumors (Bondy et al., 2008). This calls for precise diagnosis and classification for effective therapy. Imaging methods, especially Magnetic Resonance Imaging (MRI), are still the most effective way of identifying problems since they provide a lot of information about the structure and function of things. People like to commend noninvasive approaches like MRI and CT as safer, but more effective than invasive techniques (Mehrotra et al., 2020).

Most recent advancements in computer-aided medical image processing have further enhanced tumor detection. Tumor segmentation, while frequently used, is invariably time-consuming and operator-dependent. Automated methods, especially those that take advantage of machine learning, are more precise and time-saving (Amin et al., 2022; Laukamp et al., 2021).

Tumor characteristics, including type, size, shape, and site of origin, directly influence survival and treatment planning, such as surgery, radiotherapy, or chemotherapy (Sathies Kumar et al., 2022). Thus, early diagnosis and precise classification are crucial in building customized treatment plans. During medical image analysis, preprocessing steps such as feature selection, segmentation, and augmentation are commonly utilized before classification tasks (Bankman, 2009). Deep learning is now a robust alternative to conventional machine learning. Compared to conventional approaches based on hand-crafted features, discriminative features in deep learning architectures are learned from raw data automatically, leading to enhanced diagnostic accuracy and robustness (Laukamp et al., 2019; J. Liu et al., 2018). The practice of comparing the proposed model with base models and other custom hybrid models to check the comparison of accuracy and robustness (Ahamed et al., 2024). Researchers often compare findings of different models to compare and find the best model for detecting disease (Trisna et al., 2024).

In this paper, MRI-based brain tumor detection is enhanced by integrating medical image processing and machine learning techniques into computer-aided diagnosis systems. Special focus of the paper is placed on comparing current methods, experimenting with new preprocessing and classification schemes, and proposing hybrid deep learning approaches. The primary contributions of this work are as follows:

- Design of a CNN–LSTM hybrid model for brain tumor classification and prediction from MRI scans, ensuring robust performance across different tumor types.
- Utilization of CNNs for noise reduction and feature extraction, enhancing MRI image quality and enabling more reliable classification.
- Comparison of the proposed model with individual CNN, Random Forest (RF), Extreme Learning Machine (ELM), and Long Short-Term Memory (LSTM) models to evaluate its robustness.
- Provision of a promising diagnostic tool that supports radiologists and healthcare professionals in making faster, more accurate decisions regarding tumor detection and treatment planning.

The remainder of this work is structured as follows. Section 2 examines relevant studies on brain tumor detection employing machine learning and deep learning methodologies. Section 3 discusses the suggested model architecture and the descriptions of the datasets. Section 4 describes the training environment and the evaluation matrices. Section 5 delineates the quantitative findings and analysis. Section 6 concludes the manuscript.

2. Literature Review

In recent years, deep learning models have made their way into brain tumor diagnosis heavily utilizing high precision with automatic feature extraction and classification. The most widely used models are Convolutional Neural Networks (CNNs), which include input, hidden, and output layers, and learning-controlling hyperparameters. CNNs generate feature maps through scanning filters over images for input, enabling automatic feature extraction without any human intervention. Despite all their success, CNN models are prone to require huge datasets, time-consuming hyperparameter tuning, and considerable computational resources for training and testing. To counter the absence of medical datasets, scientists have employed data augmentation methods such as rotation, scaling, transformation, and resizing (Lakshmi & Nagaraja Rao, 2022). Transfer learning (TL) has also been extensively used, utilizing pre-trained networks such as ResNet, VGGNet, GoogleNet, and AlexNet to acquire transferable features from MRI datasets to improve classification performance using sparse medical data (Mehrotra et al., 2020).

Brain tumors, benign or malignant, disrupt normal brain function and can rapidly spread with extensive resultant neurological injury. Tumors of malignant nature are even more so due to their invasive nature and aggressive growth characteristics (Fernando et al., 2022; Jun & Liyuan, 2022; Lakshmi & Nagaraja Rao, 2022; Rehman et al., 2020). Early detection and accurate classification are essential in improving survival and selecting the appropriate type of treatment. Tumor detection, however, remains challenging with significant tumor shape, size, location, and appearance variability, not to mention scanning conditions and modalities variability (Lundervold & Lundervold, 2019). Traditional methods of diagnosis, such as the Leksell Gamma Knife and radioactive beam techniques, have also been applied to the detection of lesions (Rundo et al., 2016), but these are experience-intensive and time-consuming. In contrast, medical imaging modalities such as Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) provide non-invasive solutions. New MRI techniques, such as Chemical Exchange Saturation Transfer (CEST), have also increased the potential to detect low-concentration biomolecules that cannot be detected by normal imaging. Nevertheless, the increasing sophistication of MRI scans are often in advance of the human visual system's capabilities, creating the necessity for computer-aided diagnostic (CAD) systems that can help radiologists detect and classify correctly. Machine learning has been a revolutionary factor in tumor detection by enhancing segmentation accuracy and classification robustness. Hybrid methods, for instance, such as Random Forest classifiers combined with voxel clustering have shown reliable lesion detection (Bonte et al., 2018), whereas semiautomated techniques based on Fuzzy C-Means (FCM) clustering have ensured precise lesion volume segmentation (Militello et al., 2015). The remaining works have proposed algorithms such as Kmeans, Gaussian Mixture Models (GMM), and Gaussian Hidden Markov Random Fields (GHMRF) for improved tumor segmentation accuracy (Juan-Albarracín et al., 2015). Additionally, necrosis extraction methods such as NeXt apply fully automated pipelines to improve lesion segmentation with FCM algorithms (Rundo et al., 2018).

A research study proposed methods based on statistical threshold patterns employing a multiscale Convolutional Neural Network (CNN) (Jiang et al., 2018). Authors attention was on the utilization of CNN models in artificial intelligence for the diagnosis of brain tumors with an accuracy of 86.30%. Another research study proposed new methods of managing multidimensional image data on network platforms using deep convolutional neural networks (DCNN) with an accuracy of 86.50% (D. Liu et al., 2018). The authors explored the use of deep Convolutional Neural Networks (CNNs) for the identification of brain tumors (Nadeem et al., 2020). The study focused on utilizing CNN-based learning methods to medical image-related tasks. The study points out the applicability of CNN architectures to clinical applications in cancer classification. Deep CNNs have also been demonstrated in recent research to be useful for the identification of brain tumors. DenseNet and DarkNet architectures, for example, have been applied to BRATS 2018 3D-MRI scan dataset with DSC scores of over 96%. DenseNet recorded an accuracy of 98.26% with DSC of 98.14%, with DarkNet recording a 96.52% accuracy and DSC of 96.44% (Gull et al., 2021). Comparative studies confirmed that DenseNet outperformed DarkNet, and custom CNN architectures deployed using Keras and TensorFlow also demonstrated improved classification accuracy. A few of these frameworks have been integrated into cross-platform clinical software, using PyQt5 for GUI design and MariaDB for database management (Abugessaisa et al., 2014), to enable proper deployment in real-world healthcare environments.

Despite these advancements, automated brain tumor detection has some limitations. MRI scans are prone to being contaminated by noise during scanning and acquisition processes (Ahmed et al., 2017; Ismael, 2018; Paul et al., 2017; Xu et al., 2015). Segmentation is further complicated by the rough, tentacle-like patterns of gliomas and other tumor types, with dispersed and overlapping regions (Ismael, 2018; Ladefoged et al., 2019; Renhao Liu et al., 2016). Besides, selecting the most suitable features, as well as how much balance between training and test data is required, remains a crucial challenge (Fabelo et al., 2019). While deep learning models come with the advantage of learning automatically features, they are computationally expensive and memory-intensive. Creating lightweight yet accurate models capable of generating sound results within shorter time windows is an open research question. The problem of distinguishing between tumors with similar radiological characteristics, such as gliomas versus strokes, reflects the continuing need for advanced classification and segmentation techniques that can address such complexities with ease.

3. Proposed Method

3.1 Dataset and Preprocessing

The Brain Tumor MRI Dataset (Nickparvar, 2021) is used in this study for the training and validation of the proposed model. This dataset is a useful collection which combines image data from three different, well-known sources-

- The figshare Dataset
- The SARTAJ Dataset
- The Br35H Dataset

There are 7,023 high-resolution MRI pictures of the human brain in the entire dataset. These pictures have been carefully divided into four classes, which correspond to the most frequent brain imaging diagnoses:

- **Glioma:** A kind of tumor that develops in the brain or spinal cord from glial cells.
- **Meningioma:** A tumor that develops from the membranes which surround the brain and spinal cord.
- **Pituitary:** A tumor that develops in the pituitary gland, which is frequently found close to the base of the brain.
- **Notumor:** Images that serve as a crucial control group and are verified to be free of any discernible tumor.

To understand how class imbalance could happen during training, it's important to know exactly how many images are in each category. Table 1 gives an overview of this composition:

Table 1. Summary of Brain Tumor MRI Dataset.

Tumor Class	Image's Numbers	Percentage (%)
Glioma	1621	23.08%
Meningioma	1645	23.42%
Pituitary	1757	25.02%
No Tumor	2000	28.48%
Total	**7023**	**100%**

As each MRI brain image contains undesirable regions and gaps, cropping the images is essential to focus on relevant information. MRI images are loaded, converted to grayscale, thresholded, and blurred to generate binary images. To remove small noise spots, dilation and erosion are used. To identify the extreme points (left, right, top), the most significant contour is determined from the thresholded image. Based on the data gathered from these extreme points and contours, the final crop will be determined. The images are then resized using bicubic interpolation, which provides smoother results than bilinear interpolation, especially for MRI images with noisy edges. The authors changed the size of every image to 150 × 150 pixels. Normalization is used to normalize and make the input data consistent, pixel values are normalized to be in the range (0, 1).

3.2 Model Architecture

The proposed approach utilizes a hybrid architecture that combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks for the purpose of classifying brain tumors. This design utilizes the CNN's proficiency in extracting detailed spatial features from MRI scans, alongside the LSTM's strength in capturing sequential or structural dependencies within the same dataset. Figure 1 illustrates the comprehensive design structure of the proposed model.

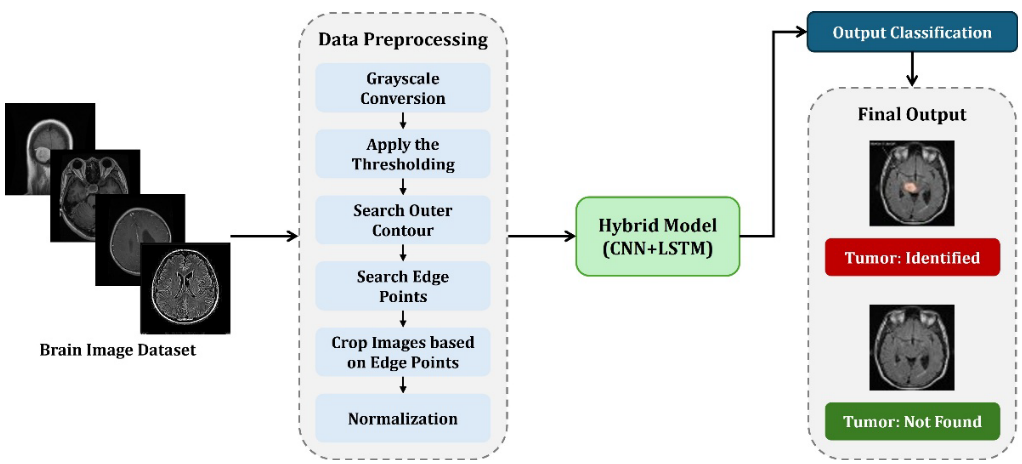

Figure 1. Proposed model architecture.

The CNN branch focuses on acquiring distinct spatial representations from the MRI images. The data comprises grayscale brain MRI slices. The architecture initiates with a convolutional layer, succeeded by a ReLU activation function to incorporate non-linearity. A max-pooling operation is subsequently implemented to decrease spatial resolution while preserving essential features. The procedure is reiterated with an additional convolutional layer, subsequently accompanied by max pooling. The feature maps obtained are flattened and subsequently processed through a fully connected layer with ReLU activation, allowing the network to grasp intricate high-level abstractions. A dropout layer is implemented at this stage to address the issue of overfitting. The CNN branch generates a concise feature vector that captures spatial details from the input MRI images. Alongside the CNN stream, an LSTM-based sequence model is utilized to capture structural dependencies by interpreting each MRI image as a sequence of pixel rows. This branch receives input in two dimensions: the first dimension indicates timesteps, while the second dimension denotes features associated with each timestep. The sequence model consists of two stacked LSTM layers. The initial LSTM layer is set up to return sequences, which maintains the temporal relationships for the layers that follow. The subsequent LSTM layer compresses the sequential representation into a more compact embedding. A dense layer is then applied, utilizing ReLU activation to generate a compact feature vector that encapsulates the sequential characteristics of the MRI scan. The outputs from the CNN and LSTM branches are combined to create a unified feature representation that incorporates both spatial and sequential information. The combined feature vector is input into a softmax classifier that has four output neurons, each representing one of the target classes: glioma, meningioma, pituitary tumor, and no tumor.

The proposed architecture effectively integrates the strengths of CNNs for spatial feature extraction and LSTMs for sequential modeling, enabling it to learn both local texture-level features and global structural dependencies in MRI images. This collaboration improves the model's capacity to precisely categorize brain tumors into four clinically significant groups.

4. Training and Evaluation Methods

4.1 Hardware and Software Setup

The experiments were run on the following hardware:

- CPU: Ryzen 7 3700X 3.6 GHz
- RAM: 16 GB DDR3
- GPU: Nvidia 2060 Super 8 GB

4.2 Hardware and Software Setup

The authors trained the proposed model on the above-mentioned dataset. The study utilized 80% of the dataset images for training and the remaining 20% for validation. The hybrid model underwent training utilizing the Adam optimizer, set with an initial learning rate of 0.0001. The categorical cross-entropy loss function was utilized to address the multi-class nature of the problem. The training process spanned 16 epochs, utilizing a batch size of 32. Validation was conducted simultaneously throughout the training process to assess model generalization and reduce the risk of overfitting.

4.3 Evaluation Metrics

To demonstrate the performance of the proposed model, the authors utilized widely used metrics in image classification works, such as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$AUC - ROC = \int_0^1 TPR(t)FPR(t)\ dt \tag{4}$$

Equations 1, 2, 3, and 4 represent the mathematical formulas to calculate the matrices used for this study. To visualize the proposed model's correct and incorrect predictions across classes, the authors used the confusion matrix.

5. Experimental Results and Discussion

The following are the results of the proposed hybrid model on the Brain Tumor MRI Dataset. The study plots the loss, accuracy and ROC values of the proposed hybrid model over 16 epochs of training and validation.

5.1 Results for The Proposed Hybrid Model

For the Brain Tumor MRI Dataset, the study observes in Figure 2 that the loss value steadily decreases over 16 epochs while the accuracy increases and stabilizes after a few epochs. The AUC-ROC values behave quite similarly to the accuracy value as they reach their maximum values after a few epochs. The confusion matrix in Figure 3 shows the correct and wrong predictions for each class in the test dataset and the model was correctly classified as most of the images.

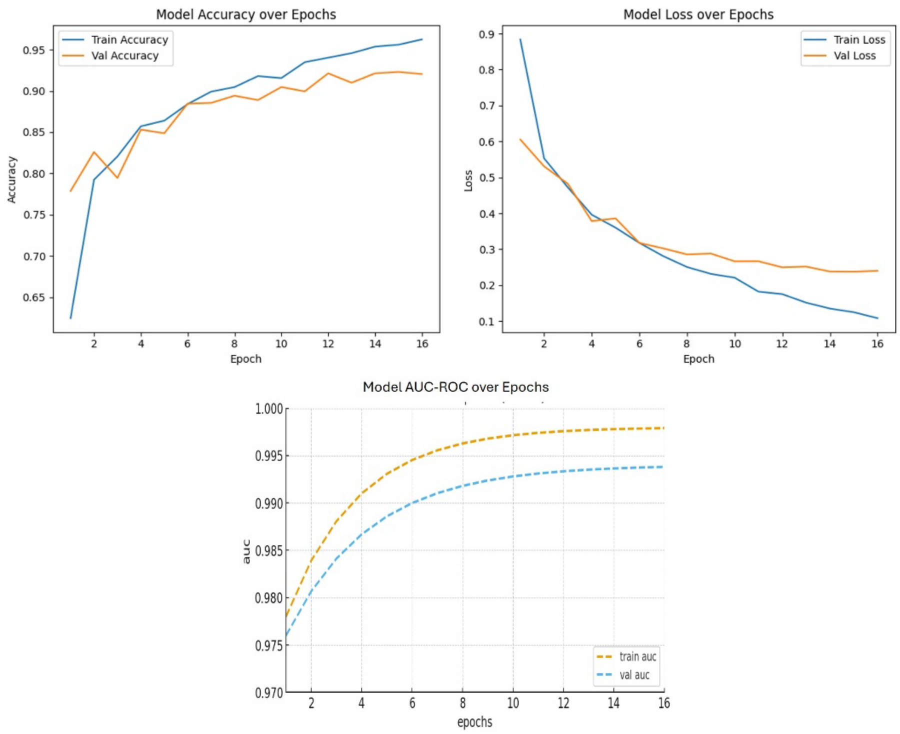

Figure 2. Accuracy, Loss, and AUC-ROC curve for the proposed model.

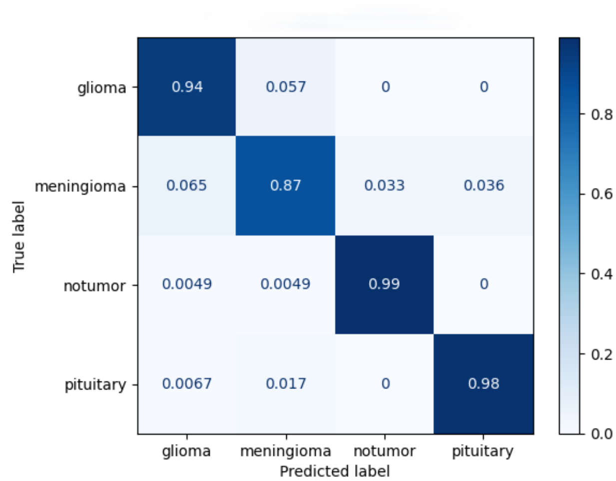

Figure 3. Confusion matrix of the proposed model.

The findings validate that the proposed approach attains satisfactory convergence and elevated classification accuracy (Figure 3).

5.2 Comparative Analysis

The authors provide Table 2 to evaluate the performance of the proposed model against other base models that were trained on the same dataset.

Table 2. Comparison of the proposed model with other models.

Model	Accuracy (%)	Precision (%)	Recall (%)
CNN	79.43	79.33	79.41
ELM	83.12	84.33	84.23
RF	92.02	92.05	92.03
LSTM	94.00	94.00	94.00
Proposed Model	**94.50**	**94.55**	**94.51**

The Proposed Model outperforms all the base models, which means that the authors' adjustments to the architecture or methods made a measurable difference in performance on this dataset. The LSTM model is the closest contender, with a high and balanced performance across all criteria. The Random Forest (RF) model does well too, especially for a model that doesn't use deep learning. The CNN (Convolutional Neural Network) and ELM (Extreme Learning Machine) models don't operate as well as the others, which means they might not be the best choice.

5.3 Limitations and Future Research

The proposed architecture shows encouraging results; however, it still has several limitations:

- The existing model has been developed using just one dataset. The need for testing generalization across various datasets, scanners, and imaging protocols persists.
- While the integration of CNN and LSTM enhances accuracy, the model functions as an unknown entity. Future investigations could go further into attention mechanisms or saliency mapping to enhance clarification.
- The dual-branch hybrid model presents increased computational complexity compared to single-branch networks, potentially restricting its implementation in resource-limited medical environments.

Future investigations should focus on broadening the dataset, integrating data augmentation methods, and utilizing explainable AI (XAI) techniques to improve clinical reliability. Furthermore, employing transfer learning with pre-trained CNN architectures such as ResNet and VGG, together with LSTMs, has the potential to enhance classification performance significantly.

6. Conclusion

This study proposed a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to identify and categorize brain cancers using MRI images. The investigation successfully navigated several challenges in tumor identification and classification through the integration of advanced algorithms, especially concerning small, irregularly shaped tumors. The CNN component played a crucial role in extracting hierarchical features from the MRI images, enhancing data representation, and minimizing noise. The model was further improved by LSTM, which effectively learned temporal patterns and dependencies essential for analyzing sequential data.

The hybrid model demonstrated superior performance compared to traditional individual models such as CNN, ELM, LSTM, and RF, achieving an impressive accuracy of 94.50%. The model demonstrated remarkable proficiency in tumor identification and classification, evidenced by its outstanding performance across various metrics, such as precision, recall, and AUC-ROC. The results indicate the potential for immediate clinical applications while also validating the effectiveness of integrating CNN and LSTM.

The results indicate that this hybrid method has the potential to greatly enhance the domain of medical imaging, especially in the automation of brain tumor diagnosis. The proposed hybrid model improves diagnostic accuracy while minimizing computational demands, making it an ideal candidate for incorporation into medical processes. This integration facilitates earlier and more dependable diagnoses, which can significantly enhance patient outcomes. In conclusion, the suggested hybrid model presents a compelling approach for classifying brain tumors, effectively addressing the conventional obstacles encountered in medical imaging.

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Biographies

Nusrat Jahan Trisna currently holds the position of Lecturer in the Department of Computer Science at American International University-Bangladesh. Before this role, she was a lecturer at City University's Computer Science and Engineering Department. She graduated with a bachelor's degree in computer science and engineering from American International University-Bangladesh in 2020. Continuing her academic pursuits, she obtained her master's degree in computer science with a specialization in information and Database Management from American International University-Bangladesh in 2023. Her research focuses on big data, particularly Database Management, AI, Data Science, and Computer Vision.

Saikat Baul currently holds the position of Lecturer in the Department of Computer Science at American International University-Bangladesh. Before this role, he was an instructor in the same department, showcasing his expertise and commitment to academic excellence. In 2022, he earned his bachelor's degree in computer science and engineering from American International University-Bangladesh, laying the foundation for his journey in the field. His academic journey continued as he pursued and completed his master's in computer science with a specialization in software engineering from American International University-Bangladesh in 2023. His research interests are diverse, focusing on Software Engineering, Machine Learning, Deep Learning and Computer Vision.

Md. Khairul Alam Mazumder now holds the position of Lecturer in the Department of Computer Science at American International University-Bangladesh (AIUB). Before his appointment at AIUB in 2024, he served as a Lecturer at Uttara University from July 2023 to January 2024, acquiring significant teaching experience. He obtained his Bachelor's degree in Computer Science and Engineering in 2021, subsequently earning a Master's in Computer Science in 2024. His research interests include Computer Vision, Machine Learning, and Software Engineering, with a commitment to discovering novel solutions and furthering technological progress.

Md. Ariful Islam has completed his Bachelor's in Computer Science and Engineering and Master's in Information & Database Management from American International University-Bangladesh (AIUB) in 2021 and 2023, respectively. He is currently working as a Lecturer of the Faculty of Science and Technology at American International University-Bangladesh (AIUB). He is interested in research areas including Federated Learning, Machine Learning, Data Analytics, Graph Theory, and a wide variety of Algorithms and Data Structures.

Farzana Bente Alam is currently working as a Lecturer in the Department of Computer Science under the Faculty of Science and Technology at American International University-Bangladesh (AIUB). She completed her bachelor's in computer science and engineering from American International University-Bangladesh in 2005 and her master's in computer science from The University of Montana, USA in 2011. Machine Learning, Software Engineering, IOT, and Blockchain are some of her areas of research interest.