Computing, Information Systems, Development Informatics and Allied Research Journal
Vol. 16 No. 3, September 2025 - www.cisdijournal.net

Development of an Artificial Intelligence-Based Brain Trauma Detection System Using Transfer Learning Models

[1*]Pius Ekwo Kekong, [2]Joseph S. Igwe, [3]Michael E. Ekpo, [4]Nicholas Adeiza Victor
[1*]Dept of Mathematics & Computer Science, Federal University of Health Sciences, Otukpo, Nigeria
[2&3]Department of Computer Science, Ebonyi State University, Abakaliki
[4]Dept of Information & Communication Tech, Federal University of Health Sciences, Otukpo, Nigeria
E-mails: [1*]piuskekong2019@gmail.com; [2]joseph.igwe@ebsu.edu,ng; [3]ekpom550@gmail.com
[4]vicholas72@gmail.com
Corresponding Author's Tel: +2348085211771

ABSTRACT

The accurate and timely detection of brain trauma is critical for effective clinical intervention in Nigeria. Hence, this study presents a deep learning-based brain trauma detection system adopting the Trans-disciplinary Research Integration Framework (TRIF) for the integration ofe insights from neuroscience, data science, and clinical medicine. Clinical and neuro-data were collected from 250 anonymized patients at the University of Nigeria Teaching Hospital and Memphis Hospital in Enugu, Nigeria, and transformed from tabular CSV format into 2D grayscale images suitable for convolutional neural network processing. Furthermore, two transfer learning models, ResNet-50 and InceptionV3, were employed as feature extractors and integrated with a Squeeze-and-Excitation Operation Module (SEOM) in order to dynamically recalibrate channel-wise features and the models were trained to classify brain trauma severity into mild, moderate, and severe categories. Evaluation results demonstrated that ResNet-50 + SEOM outperformed InceptionV3 + SEOM, achieving an accuracy of 97%, a loss of 0.06, and superior precision, recall, and F1-scores across all trauma classes. These findings highlight the effectiveness of combining advanced deep learning architectures with attention mechanisms for robust, clinically relevant brain trauma classification, providing a foundation for real-time diagnostic support in healthcare settings.

Keywords: Brain Trauma; Deep Learning; Transfer Learning; ResNet-50; InceptionV3

CISDI Journal Reference Format
Pius Ekwo Kekong, Joseph S. Igwe, Michael E. Ekpo, Nicholas Adeiza Victor (2025): Development of an Artificial Intelligence-Based Brain Trauma Detection System Using Transfer Learning Models. Computing, Information Systems, Development Informatics and Allied Research Journal. Vol 16 No 3, Pp 7-24 Available online at www.isteams.net/cisdijournal.
dx.doi.org/10.22624/AIMS/CISDI/V16N4P2

1. INTRODUCTION

Neurological Disorder (ND) is a broad spectrum of conditions that affect the central nervous system, disrupting normal neurological functions in either the brain, nerve or spinal cord (Zammit *et al.,* 2021). Neurological Disorder (ND) includes brain trauma, epilepsy, Parkinson's disease, Alzheimer's disease, brain tumor and stroke (Feigin *et al.,* 2020). While these ND diseases mentioned are very dangerous and requires intensive care and management, Brain Trauma (BT) has continued to dominate health related literatures (Hosseinali *et al.,* 2023; Yazdan *et al.,* 2022; Chandan et al., 2020). For instance, in 2019, 27.16million cases of BT was reported worldwide (Xiao *et al.,* 2024; Guan *et al.,* 2023).

Pierre et al. (2024) further revealed that an average of 250 persons are infected with BT in every 100,000 individual all over the world, and contributes to about 50% of all trauma related injuries. Brain trauma is a non-degenerative and congenital effect on the brain, due to incidence such as physical assault, or accident, leading to temporal biochemical imbalance in the flow of axoplasmic within the intracellular neurofilament (Alouani and Elfouly, 2022). Brain Trauma Injury (BTI) is of three main types which are the intracranial hematoma, intracranial pressure and midline shift (Alouani and Elfouly, 2022). One major challenge of BT related studies is to achieve early prognosis, considering the best predictors of outcome, to facilitate administration of effective treatment (Bruschetta *et al.,* 2022). Early and accuracy detection of BT is a critical step in the successful management of the problem, and prevention of the potential life-threatening situation arises late discovery.

Traditional approaches for the management of BT involves the application of concussion assessment tool and Glasgow coma scale for measuring symptoms such as seizure, amnesia, concussion, headache and psychiatric health records (Alouani and Elfouly, 2022). Most recently, the application of Artificial Intelligence (AI) in health care has greatly improved quality of patient management through accurate prediction and diagnosis of diseases (Igwe *et al.,* 2021). Deep Learning (DL) which is branch of A.I has continued to dominate studies on medical image classification problems, exploring the huge volume of big data (Ajah and Nweke, 2019) in the health care sector to improve quality of service.

According to Kekong *et al.* (2022), DL as a sub-field of Machine Learning (ML) has the potential for high accuracy and efficiency in medical image analysis. In the context of neurological disorder, researchers have made significant number of contributions, applying DL for the image analysis; however, Pierre *et al.,* (2024) revealed that limited studies were focused particularly on BT, thus necessitating the need for more studies in this field. Notable studies who applied DL for BT include Monteiro (220) who trained Convolutional Neural Network (CNN) for the classification of intracranial haemorrhages, recording sensitivity of 80% and specificity of 90% respectively.

Both Nag (2021) and Yan (2022) employed CNNs for midline shift estimation, achieving commendable accuracies greater than 85% and consistency across different types of intracranial haemorrhages, while Pease *et al*., (2022) combined a fusion of CNN based analytical data with a clinical model to forecast six months' outcome of BT, and recorded high prediction success which supersedes traditional IMPACT models. While these studies have demonstrated the effectiveness of DL in medical image analysis, Chae and Kim (2023), argued that DL suffers several problems which include huge requirements of training data, high cost of resources, resource intensive, and hence performance degradation.

Transfer Learning (TL) has emerged as an improved version of DL, allowing already trained models on large scale to be applied in solving new classification tasks (Chidi *et al.,* 2024). However, (Gu ad Lee, 2024; Salehi *et al.,* 2023) revealed that medical images present unique problems due to the inherent features such as grey scale, high dimensionality, high resolution and anatomical structures (Yu et *et al.,* 2022; Shamshad *et al.,* 2023; Malhotra *et al.,* 2022), thus raising a research question on how can TL be fine-tuned for more accurate medical image classification? To solve this problem in the context of BT image classification, Guimaraes *et al.,* (2022) proposed one dimensional convolutional machine learning and 1D CNN and recorded 0.889 classification accuracy.

Abdullah *et al.* (2024) trained a fusion of advanced wavelet transformation fusion algorithm and Convolutional Neural Network-Vision Transformer (CNN-ViT). The research recorded 99.8% accuracy, which is good, but despite the success, Mcdonald *et al.* (2024) and Covingto and Duf, (2021) opined that heterogeneity of BT data were never considered and are often states as limitation of studies in existing literatures. In addition, there is need for a model which is specifically tailored towards the characteristics features of BT images to facilitate maximum feature identification and extraction for image analysis. This is because most of the existing model always applied the traditional working principles of the TL, without considering its efficiency on poor medical image qualities, thus raising a second research question of how can feature extraction of medical images be optimized in TL model? To answer this question, this study proposes the development of an improved transfer learning model for early detection and diagnosis of neurological disorders.

2. RESEARCH METHODOLOGY

The methodology used for this study is the Trans-disciplinary Research Integration Framework (TRIF). TRIF is a structured approach that integrates insights from multiple disciplines to address complex and multifaceted problems. In this study, TRIF unites expertise from neuroscience, data science, and clinical medicine to develop a robust brain trauma detection system using deep learning. The framework supports the systematic integration of diverse datasets, including neuro-data scans with advanced deep learning techniques. This methodology was chosen because of its ability to foster collaboration across domains, ensuring that the solution is not only technically sound but also clinically relevant and practical. TRIF also facilitates iterative design and validation processes, allowing researchers to refine the system based on real-world feedback. By leveraging the strengths of multiple fields, TRIF ensures that the developed system addresses the critical challenges of diagnostic accuracy, early detection, and clinical applicability in brain trauma cases.

2.1 Data Collection

The dataset used for this study was collected from two major healthcare facilities: the University of Nigeria Teaching Hospital (UNTH) and Memphis Hospital, both located in Enugu, Nigeria. UNTH is situated at latitude 6.4300°N and longitude 7.5016°E, while Memphis Hospital lies within latitude 6.4302° N and longitude 7.5113° E. The dataset includes 250 anonymized records of patients with various degrees of brain trauma over a period of three years.

Each record comprises a comprehensive set of attributes critical for evaluating brain trauma severity, including clinical assessments like Eye Opening Response (scale 1 to 4), Verbal Response (scale 1 to 5), Motor Response (scale 1 to 6), and additional symptoms such as headache, dizziness, nausea, memory loss, and pupil dilation. The data was collected and stored in CSV format to ensure ease of integration and preprocessing. Ethical clearance was obtained for data usage, ensuring patient confidentiality and data integrity throughout the research process. Collectively the distribution of the primary data was presented in the table 1.

Table 1: Table of Data Distribution

Attribute	Data Type	Description
Patient_ID	Integer	A unique numeric identifier assigned to each patient to ensure anonymity and facilitate data tracking.
Age	Integer	The age of the patient in years, important for understanding trauma risk profiles and treatment approaches.
Eye_Opening_ Response	Integer	The patient's eye-opening reaction to external stimuli, a key component of the Glasgow Coma Scale (GCS).
Verbal_Response	Integer	The patient's ability to speak and respond verbally, assessing neurological function as part of GCS scoring.
Motor_Response	Integer	Measures the patient's motor reaction to stimuli, another critical GCS component to evaluate trauma severity.
Headache	Categorical	Indicates whether the patient reported experiencing headaches post-trauma, providing insights into injury impact.
Dizziness	Categorical	Captures if the patient experienced dizziness, an important neurological symptom linked to trauma severity.
Nausea	Categorical	Records the presence of nausea, which can be an indicator of concussion or head injury severity.
Memory_Loss	Categorical	Indicates whether the patient reported amnesia, another neurological symptom critical for diagnosis and severity classification.
Pupil_Dilation	Categorical	Measures the condition of the pupils post-trauma, used to assess brain pressure and potential damage.
Cause_of_Trauma	Categorical	Records the reported cause of the brain trauma event, providing context for analyzing common injury patterns.
Severity	Categorical	The final classification of brain trauma severity based on clinical and observational indicators, typically categorized as mild, moderate, or severe.
GCS_Score	Integer	The final calculated Glasgow Coma Scale score, a numeric assessment (sum of Eye, Verbal, Motor) of overall neurological function.

2.1.1 2D Data Transformation

The collected data, initially in tabular CSV format, was transformed into 2D grayscale images. This step was crucial as it allowed the integration of convolutional neural networks (CNNs), which excel at processing 2D image data. By converting the data into 2D grayscale images, we ensured the models could leverage their spatial feature extraction capabilities, representing each patient's diagnostic data as a structured image for consistent analysis.

2.1.2 Min-Max Normalization

Prior to feeding the images into the models, min-max normalization was applied to the pixel values of the 2D images. This normalization technique scaled the grayscale pixel values to a [0, 1] range, standardizing the input and enabling the models to converge faster and more effectively during training. This step ensured that the data variability across different samples was minimized, making it easier for the deep learning models to learn consistent patterns.

2.1.3 Data Normalization Method

Data normalization is a critical pre-processing step to achieving accurate results when evaluating deep-learning models (Tokareva *et al.,* 2024). Normalization involves transforming the data into a specific range, thus improving model performance when performing a classification problem (Albert et al., 2023). In this work, the Min-Max normalization method was applied for this work. It scales all data points between 0 and 1 using the minimum and maximum feature values. Equation 1 presents the data normalization model.

$$X' = \frac{X - \min(X)}{\max X - \min X} \qquad (1)$$

Where X is the input data, X' is the normalized data.

2.2 The Transfer Learning Model For Classification Of Brain Trauma

Transfer learning model used for the work is ResNet and Channel Attention mechanism (CAM). The ResNet was applied for feature extraction, while the CAM was applied as the classifier.

2.2.1 The ResNet Modelling

ResNet are deep learning model developed with the aim of addressing the challenges of training complex deep learning models (He *et al.,* 2016). The main component of the ResNet are the residual blocks with integrated identity mappings to allow the learning of residual functions instead of differently training every layers of the network. The architecture of simple ResNet is presented in Table 2 with several components which are the convolutional layers, the batch normalization, and Rectified Linear Unit (ReLU) activation. The core idea of residual block is presented as Equation 1

$$y = F(x, \{W_i\}) + x \qquad (2)$$

Where X is the input, y is the output, $\{W_i\}$ is the parameter of the residual function, $F(x, \{W_i\})$ represent the residual function to be trained, and is made of the several layers of neural network. For nth layered residual block, the specific form is defined as Equation 3 (Xu *et al*., 2024; Zhang *et al.,* 2023));

$$F(x, \{W_i\}) = W_n \sigma(W_{n-1} x) \qquad (3)$$

Where W_n the total layers of the residual blocks are, W_{n-1} is the previous layer, σ is the activation function. The equation 3 in a stacked form is reported as Equation 4 (Zhang et al., 2023);

$$y_l = F(y_{l-1}\, \{W_i\} + y_{l-1} \qquad (4)$$

Where y_l is the output of the l-th layer, $F(y_{l-1}\, \{W_i\})$ is the residual function of the l-th layer, and y_{l-1} is the output of the (l-1)-th layer. The architecture of the ResNet-50 is presented in table 3, while the output size is calculated with Equation 5.

$$Output\ size = \frac{Input\ size + \ *Padding - kernal\ size}{Stride} + 1 \qquad (5)$$

Table 2: Architecture of ResNet-50 feature extractor

Layer Name	Kernel Size / Stride / Padding	Input Size (C, H, W)	Output Size (C, H, W)
Input	-	(3, 640, 640)	(3, 640, 640)
Conv1	7×7 / 2 / 3	(3, 640, 640)	(64, 320, 320)
MaxPool	3×3 / 2 / 1	(64, 320, 320)	(64, 160, 160)
Conv2_x (3 blocks)	-	(64, 160, 160)	(256, 160, 160)
Conv3_x (4 blocks)	- / 2 / 0 in first block	(256, 160, 160)	(512, 80, 80)
Conv4_x (6 blocks)	- / 2 / 0 in first block	(512, 80, 80)	(1024, 40, 40)
Conv5_x (3 blocks)	- / 2 / 0 in first block	(1024, 40, 40)	(2048, 20, 20)
Global Avg Pooling	- (avg over 20×20)	(2048, 20, 20)	(2048, 1, 1)

The ResNet-50 feature extractor processes input image through a series of convolutional and residual blocks designed to maintain important information across layers. Starting with a 7×7 convolution that captures low-level features, the model progressively applies residual blocks grouped into four main stages, each down sampling the feature maps while deepening the network. At each down sampling stage, the spatial size is halved and the number of channels (features) is doubled, preserving a balance between spatial resolution and feature richness. The final output of the extractor is a feature map of shape (2048, 1, 1), effectively yielding 2048 features that comprehensively represent the input image. These 2048 features are highly informative, capturing hierarchical and abstract patterns essential for brain trauma detection.

2.2.2 InceptionV-3 Model

Inception-v3 introduces a series of Inception modules that operate on different kernel sizes simultaneously (such as 1×1, 3×3, 5×5), combining these feature maps to create rich, multi-scale representations of the input image. This allows the network to learn both fine and coarse features while reducing computational cost. Additionally, it applies factorized convolutions, auxiliary classifiers, and label smoothing to improve convergence and generalization.

Table 3: Architecture of brain trauma

Layer Name	Kernel / Stride / Padding	Input Size (C, H, W)	Output Size (C, H, W)
Input	-	(3, 299, 299)	(3, 299, 299)
Conv1	3×3 / 2 / valid	(3, 299, 299)	(32, 149, 149)
Conv2	3×3 / 1 / valid	(32, 149, 149)	(32, 147, 147)
Conv3	3×3 / 1 / same	(32, 147, 147)	(64, 147, 147)
MaxPool1	3×3 / 2 / valid	(64, 147, 147)	(64, 73, 73)
Conv4	1×1 / 1 / same	(64, 73, 73)	(80, 73, 73)
Conv5	3×3 / 1 / valid	(80, 73, 73)	(192, 71, 71)
MaxPool2	3×3 / 2 / valid	(192, 71, 71)	(192, 35, 35)
Inception-A ×3	-	(192, 35, 35)	(288, 35, 35)
Reduction-A	-	(288, 35, 35)	(768, 17, 17)
Inception-B ×4	-	(768, 17, 17)	(768, 17, 17)
Reduction-B	-	(768, 17, 17)	(1280, 8, 8)
Inception-C ×2	-	(1280, 8, 8)	(2048, 8, 8)
Global Avg Pooling	-	(2048, 8, 8)	(2048, 1, 1)

In Table 3 which presents the architecture, it processes the input image (299×299×3), passing it through multiple convolutional, pooling, and Inception modules, and finally reduces the spatial dimensions through global average pooling to produce a 2048-dimensional feature vector that represents the high-level characteristics of the brain trauma data.

2.2.3 The Channel Attention Mechanism

The type of attention mechanism applied for this work is the Squeeze and Excitation Operation Module (SEOM). The SEOM enhances the representational power of convolutional neural networks by learning to recalibrate channel-wise feature responses dynamically (Yang et al., 2023). It operates through three main components: squeeze, excitation, and scale as shown in Figure 1.

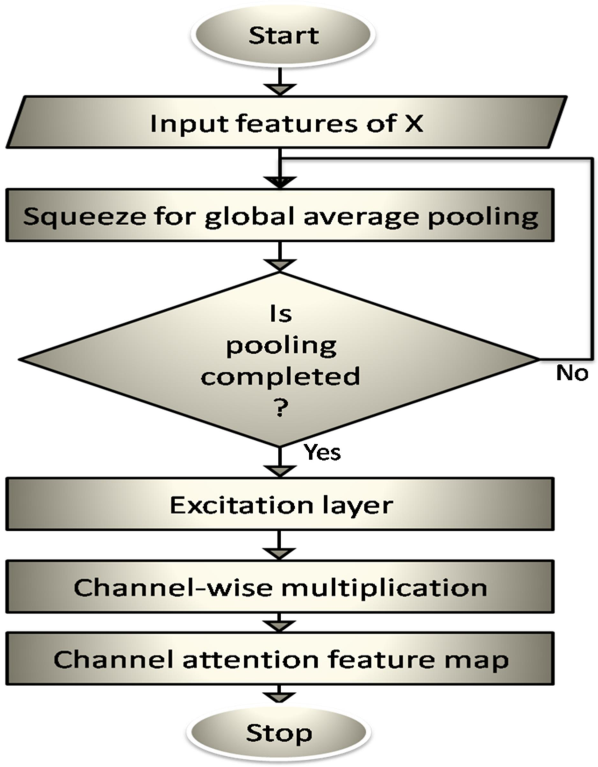

Figure 1: Flowchart of the SEOM

In Figure 1, first, the squeeze uses global average pooling to condense spatial information of each channel into a single descriptor, capturing the global context of the feature map. This reduces the spatial dimensions, yielding a channel-wise summary vector. Next, the excitation step models channel-wise dependencies by passing this vector through a bottleneck of two fully connected layers separated by a ReLU activation; the first layer reduces the dimensionality (often using a reduction ratio like 16) to form a lightweight representation, while the second expands it back to the original number of channels. Finally, a sigmoid activation produces channel-wise weights between 0 and 1, which are used in the scale step to adaptively reweight the original feature maps by element-wise multiplication. This adaptive scaling prioritizes more informative channels while suppressing less useful ones, allowing the network to emphasize relevant features dynamically based on the global context of the input.

Stepwise of the SEOM

1. **Input:** The feature map from the CNN that needs to be refined.
2. **Squeeze:** Uses global pooling to compress each channel's information into a single value.
3. **Excitation:** Two small fully connected layers learn how important each channel is, using ReLU and sigmoid activations.
4. **Scale:** This calculated the importance of each feature channels
4 **Output:** The final result is a new version of the feature map where important features stand out more clearly, making the network's next decisions even better.

2.3 System flowchart integrating the deep learning extractor with Attention mechanism

This section presents the system flow chart which integrated the deep learning extractor developed with the ResNet-50 and also the second extractor developed with Inception-V3. The reason was to experiment among the two models and then select the best for the better classification of brain trauma. In this context, the respective extractors are individually integrated with the channel attention mechanism. Figure 2 presents the integrated ResNet-50 with the channel attention mechanism while Figure 3 presents the integrated Inception-V3 with the channel attention mechanism.

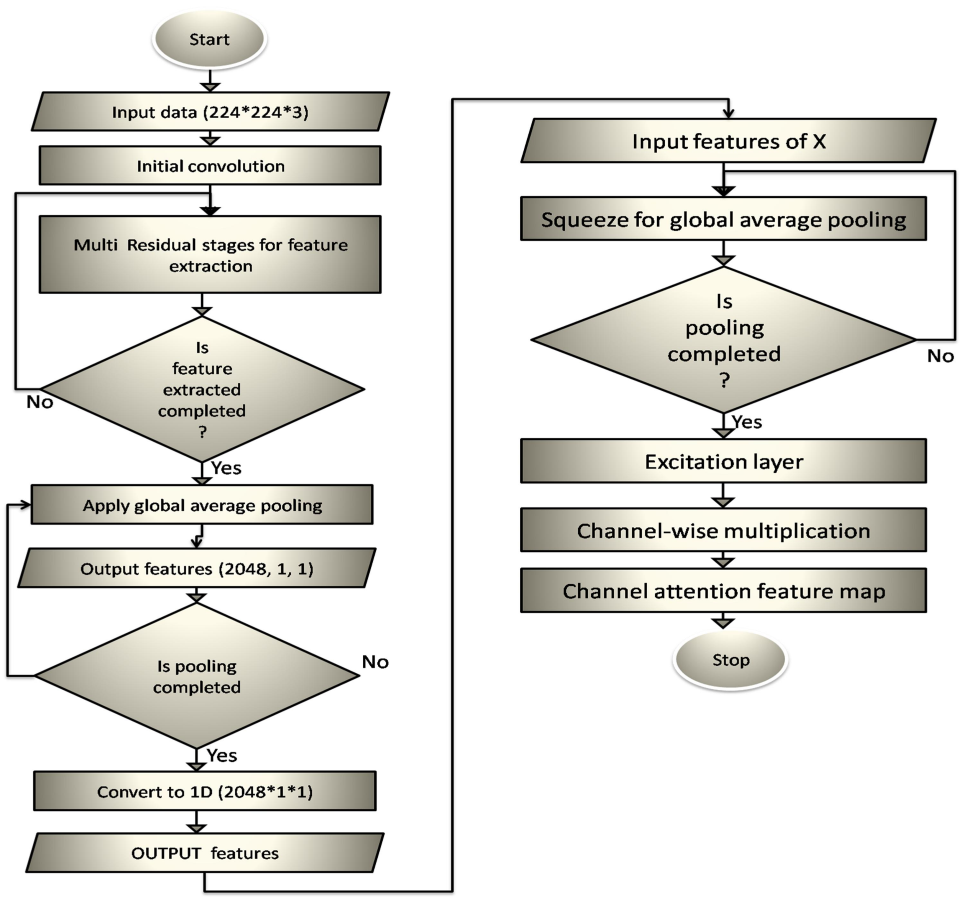

Figure 2: Flowchart of integrated ResNet-50 with the channel attention mechanism

In the Figure 2, the ResNet-50 was applied for feature extraction, while the Channel attention mechanism was applied as the classifier. In figure 4, the Incpetion-V3 was applied as the extractor while the channel attention mechanism was applied as the classifier. Individually these models after training are trained with the brain trauma data transformed with the 2D grayscale techniques and then normalized to produce the model for the detection of traumatic injury of the brain

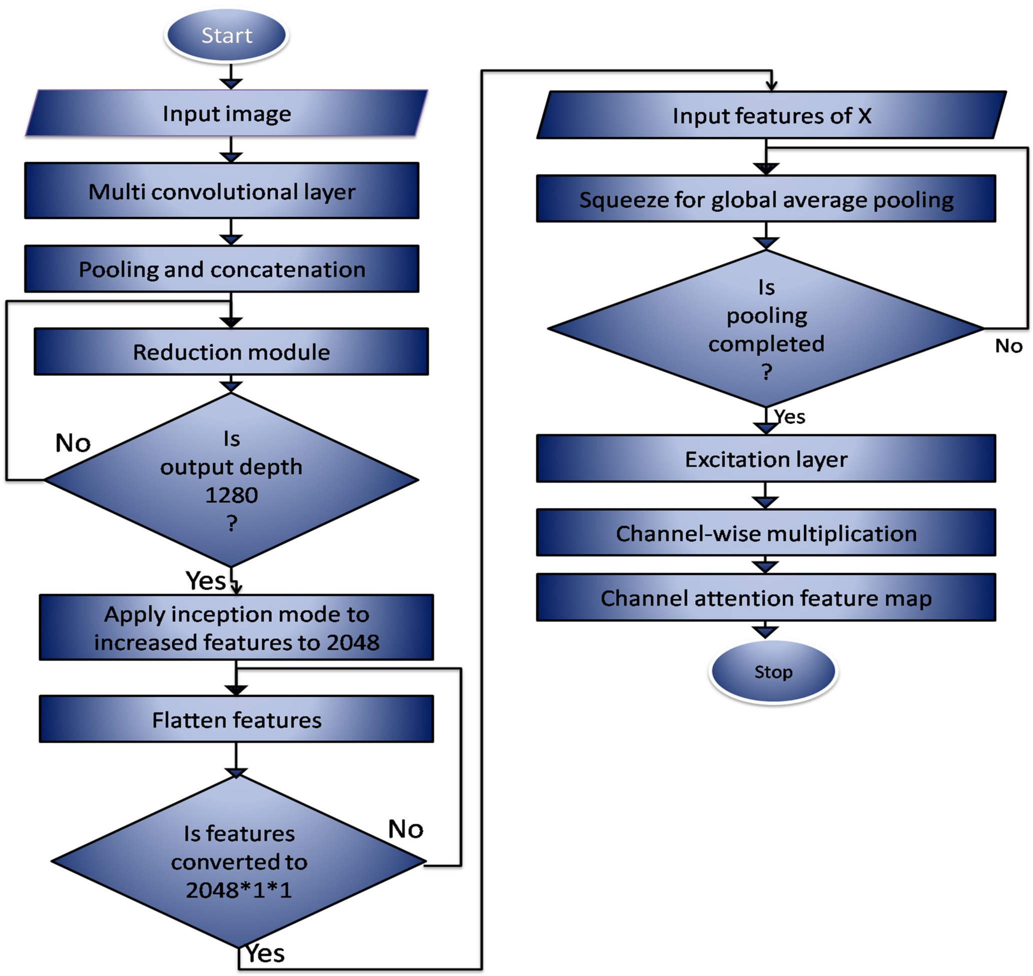

Figure 3: Flowchart of integrated Inception-V3 with the channel attention mechanism

2.4 The transfer learning model for classification of brain trauma

The model begins by taking in 2D grayscale brain trauma images as input. These images are first resized and normalized to ensure consistency and enhance feature extraction. The pre-processed images are then passed through the ResNet-50 backbone, which acts as a powerful feature extractor. The ResNet backbone uses its stacked convolutional and residual layers to detect complex and hierarchical patterns in the images like tissue textures, shapes, and edges ultimately outputting deep feature maps that encode the rich representations of the input images. Figure 4 presents the flowchart.

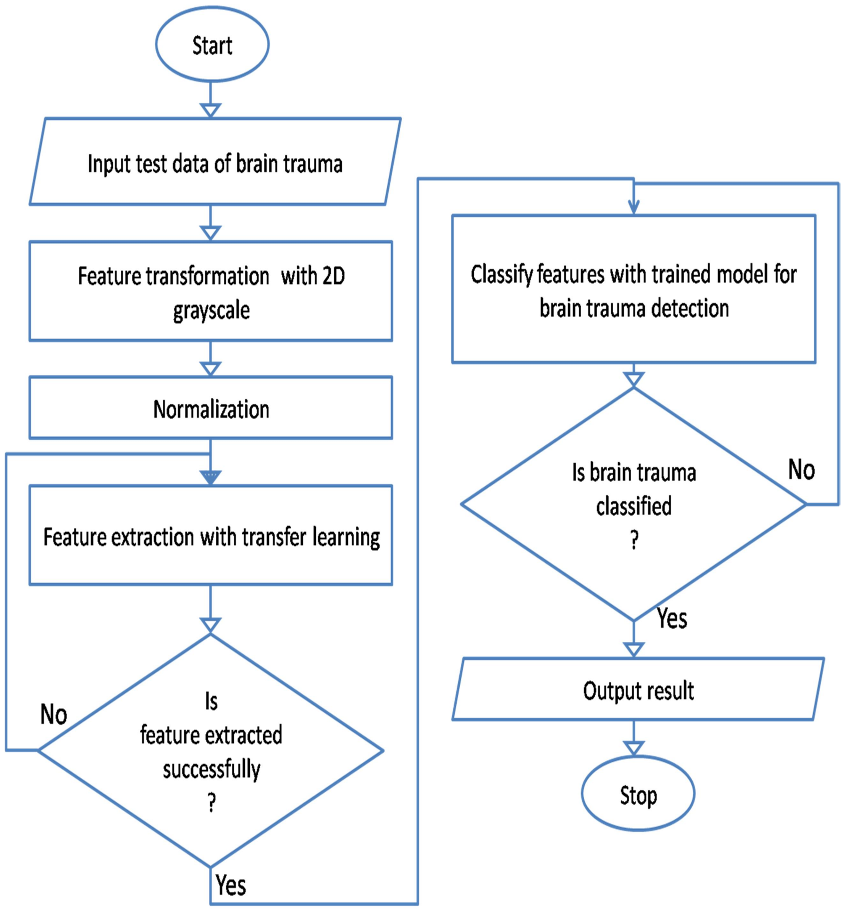

Figure 4: Flowchart of the transfer learning model for brain trauma classification

These extracted feature maps then feed into the SEOM. The SEOM block performs a global pooling operation to “squeeze” the spatial information of each channel down to a single descriptor, capturing global context. It then passes these descriptors through small fully connected layers, which use activation functions (ReLU and sigmoid) to learn how important each channel is for identifying brain trauma in the dataset. The resulting weights are then used to “excite” the feature maps by scaling the channels, so that the most relevant channels are amplified while irrelevant ones are suppressed. This ensures that only the most informative features are prioritized for classification.

Finally, the recalibrated feature maps go through more fully connected layers to produce the final prediction such as identifying the trauma type, GSC and severity class. Since the ResNet-50 weights are frozen, they provide strong general features, while the SE block and classifier layers remain trainable and adapt to the specific nuances of brain trauma data. Throughout training, only the SE block and classifier are updated, making the process efficient and robust, especially for smaller or specialized datasets.

3. PERFORMANCE EVALUATION

The performance evaluation of the model discussed the results of the different modules. The result of the data distribution is reported in Figure 5. This result showed how the different data were analyzed showing their respective distributions across attributes. Figure 28 showed the distribution of the attributes of the data such as age, GCS score, oxygen, blood pressure, hospital stay duration. The data was transformed with the 2D grayscale techniques and then applied to train the two different transfer learning model. Figure 6 presents the results of the 2D extractors.

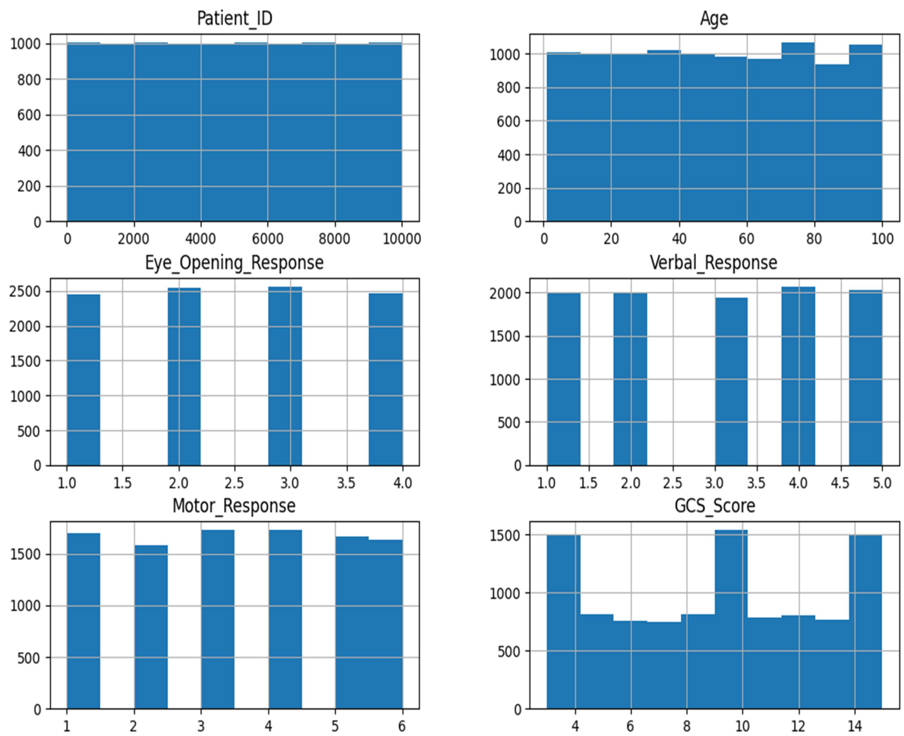

Figure 6: Result of the brain trauma data distribution

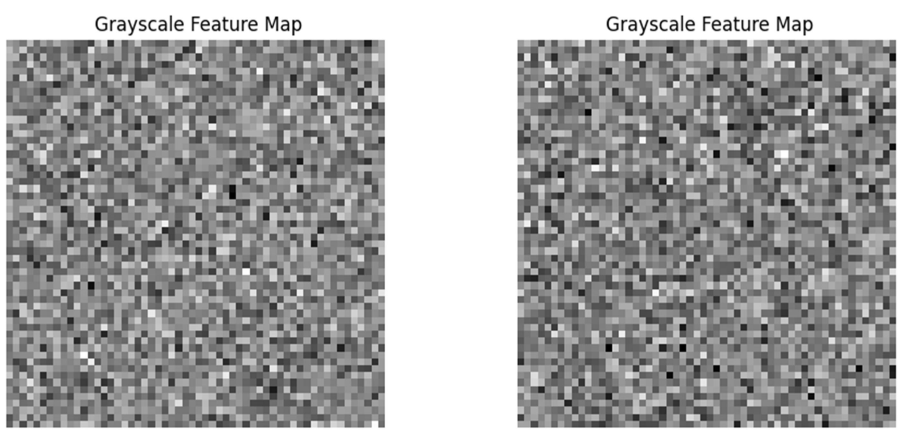

Figure 7: Result of the 2D grayscale techniques

Figure 7 presents the performance of the 2D grayscale techniques. This approach transformed the CSV formatted data into image vector as shown in the diagram with different feature maps. In Figure 8, the feature maps are extracted and reported. The results are generated by processing the grayscale images through ResNet+SE and InceptionV3+SE architectures. For each input image, feature maps are obtained by applying these pre-trained models, capturing the most salient features of the brain trauma detection dataset. The heat map visualizes the spatial intensity of the extracted features, highlighting regions of the gray scale images where the models focus their attention. The color map was used to represent the magnitude of these activations, with higher intensities depicted in warmer colors. These heat maps clearly demonstrate how each architecture emphasize different regions, revealing the unique interpretability of their feature extraction processes. Figure 8 present the training performance of the transfer learning models. Before the training, the feature extractors which are ResNet-50 and Inception-V3 are respectively freeze and then trained the SEOM across 20 epochs.

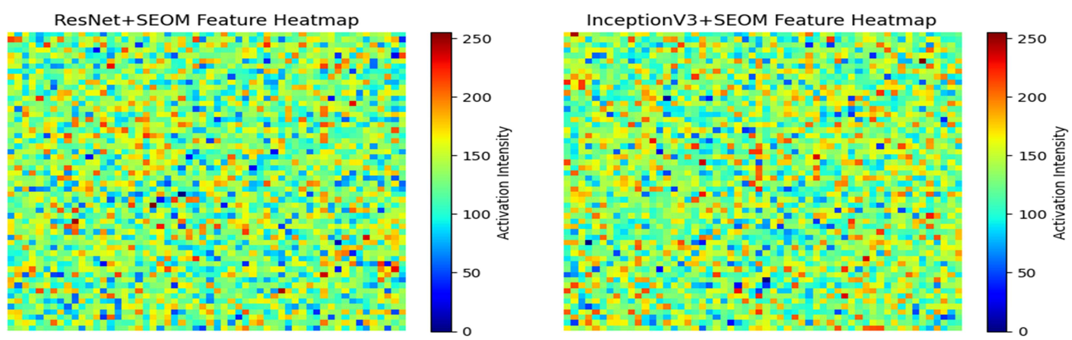

Figure 8: Result of the feature transformation with transfer learning

Figure 8 presents the accuracy of the transfer learning model. The ResNet based SEOM recorded 0.97 as the accuracy score over 20 epochs. The results implied that during the training process, the model was able to correctly classify brain trauma features in three different classes which are severe, mild and moderate with 97% success rate. The results also recorded 0.95 score of accuracy for inception-V3. The performance implied 95% success rate in correctly classifying brain trauma. Figure 9 presents the results of the model showing the stopping point.

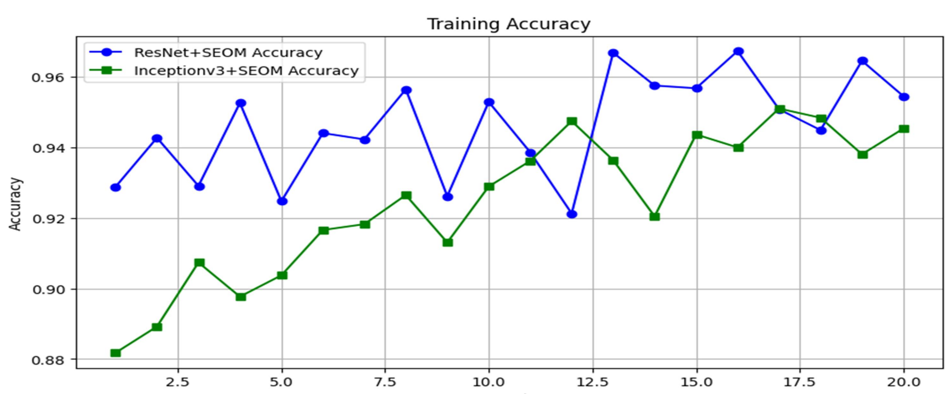

Figure 9: Result of the deep learning training process (Accuracy)

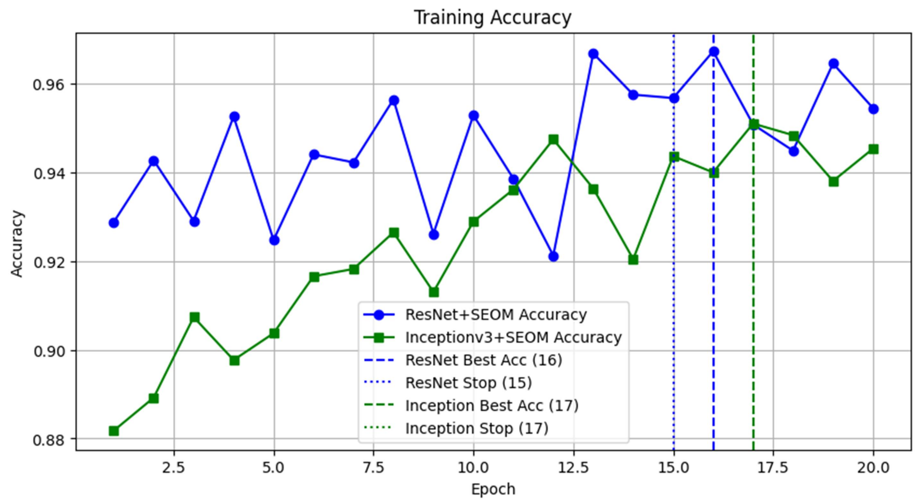

Figure 10: Result of the model ResNet-50+ SEOM Model training

Figure 10 presents the model training performance, showing the stopping point during the training. The blue lines showed that the stopping point is at epoch 16 or the ResNet which reported 97% accuracy, while the green line indicates the stopping point or the Inception model at epoch 17 which recorded 95% success rate. The loss in Figure 11 measures the error which occurred during the model training. From the results, it was observed that ResNet achieved least error at epoch 18 and then stops to generate the model at epoch 15. The loss value is 0.06, which implied 6% error of correctly classifying brain trauma. For the inception loss, it stopped at 17 with 0.17 loss which implied 7.1% false classification. Comparatively, the results showed that the ResNet based SEOM achieved better result in correctly extracting and classifying brain trauma injury. In Figure 12, the confusion matrix which analyzes the true positive and false negative of the models are respectively presented.

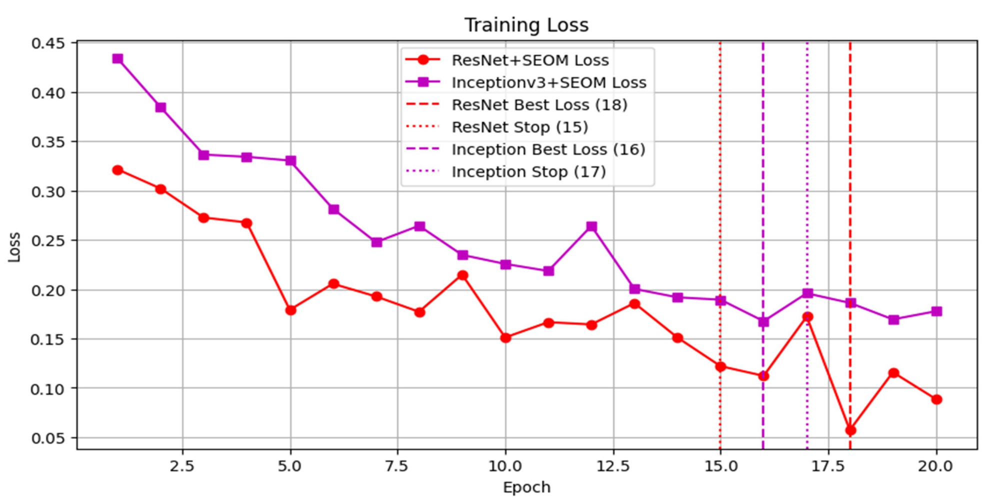

Figure 11: Result of the training process (Loss)

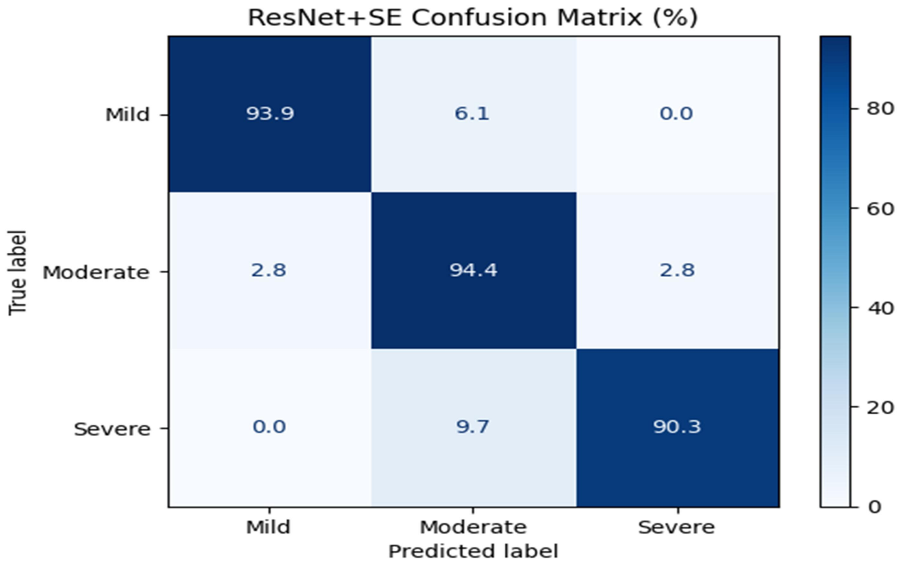

Figure 12: Result of the ResNet+ SE confusion matrix

Figure 12 presents the confusion matrix of the ResNet+SEOM across different class prediction. From the results the three main classes of the dataset target were applied to test the model. The precision when tested with mild data recorded 93.9% while the negative prediction recorded 6.1% for moderate and 0% or severe data. For moderate data test, the model recorded 94.4% success, then 2.8% false prediction on mild and 2.8 false prediction of severe features. The severe classes recorded 90.3% positive classification, 9.7% false prediction of moderate and 0% mild prediction error. The confusion matrix in figure 13 also reported the result of the inception-V3 + SEOM.

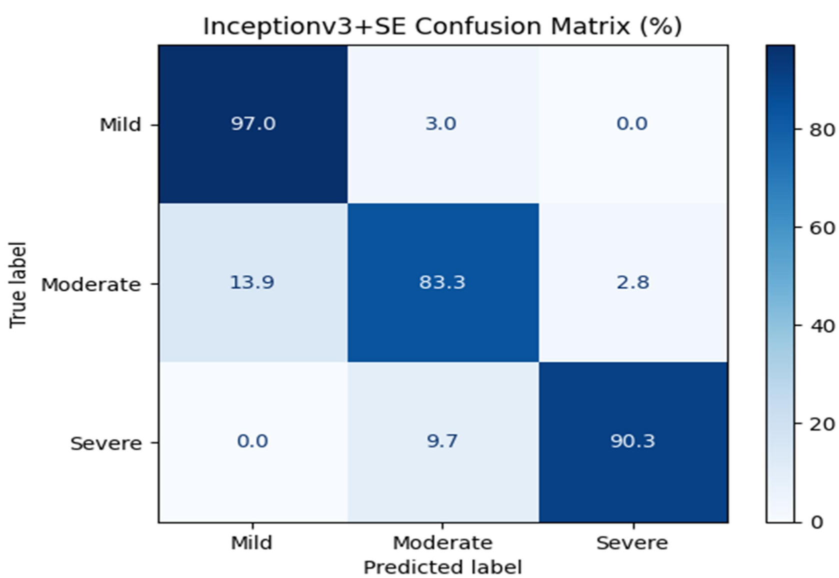

Figure 13: Confusion matrix of incepton-v3 classifier

Figure 13 recorded the precision performance of the inception-V3 model. Mild features recorded 97% correct classification of mild brain trauma. When tested with moderate brain trauma features, it recorded 83.3% success rate and when tested with severe brain trauma features, recorded 90.3% precision. Figure 36 recorded the result for precision, recall and f1-score. Precision recorded the performance of the model in correctly classifying the different brain trauma features, recall recorded the actual brain trauma classified instances and f1-score measures the harmonic mean between precision and recall. The results are reported for ResNet+ SEOM and for inception-v3 + SEOM.

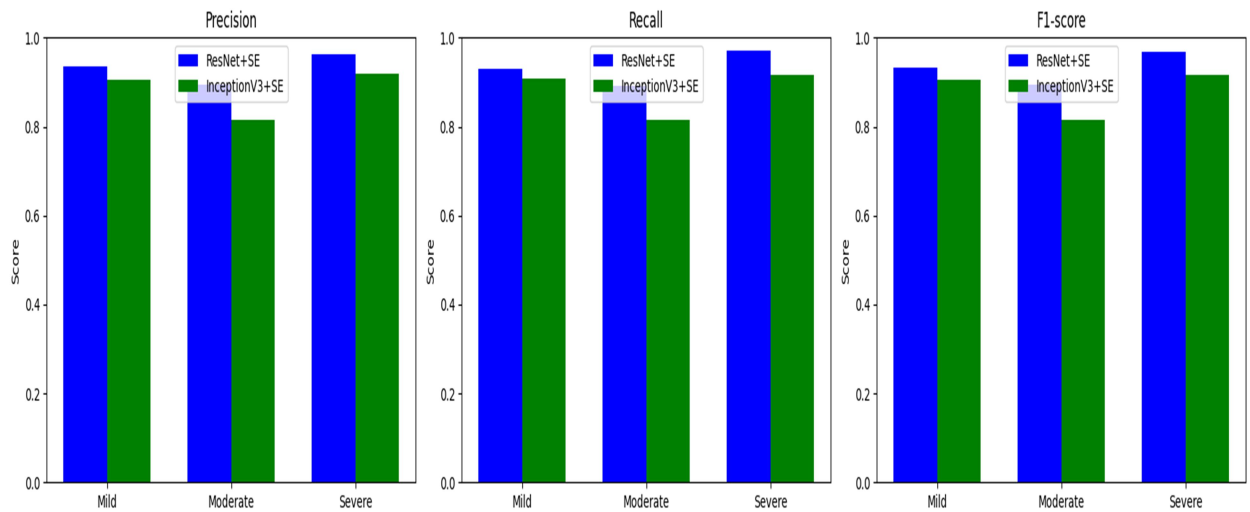

Figure 14: Result of the model performance

The result in Figure 14 presents the recall, precision and F1-score of the model performance. For precision of ResNet, the mild features recorded 93.9%, moderate features recorded 94.4% and severe features recorded 90.3%. Inception-v3 recorded 97% precision for mild features, 83.3% for moderate features and 90.3% for severe brain trauma classification. Recall for ResNet reported for mild data 93% against inception which recorded 90%. Moderate features recorded for ResNet 90% and 79% for Inception model, while severe data recorded for ResNet 98% and then 90% for inception-v3. The f1-score measures the harmonic mean between the recall and precision. For the mild features of brain trauma, the score reported 93% for ResNet and 90% for inception-v3. Moderate features recorded 90% and 80% for inception-v3. Severe features recorded 98.7% for ResNet and 91% for inception-v3.

4. CONCLUSION

In this study, a brain trauma classification model was successfully developed. Two deep feature extraction techniques from ResNet-50 and Inception-v3, integrated with a Squeeze-and-Excitation (SEOM) attention mechanism were experimented. The dataset used included essential brain trauma attributes such as Eye Opening Response, Verbal Response, Motor Response, and additional clinical observations like headache and dizziness status. Images were generated from structured patient data, pre-processed using 2D grayscale techniques, and normalized before feature extraction. The models were trained using the transfer learning to ensure robust feature representation and classification, with extensive evaluation metrics including accuracy, precision, recall, F1-score, and confusion matrix providing insights into performance and reliability.

The results from the developed model highlight the significant role of deep learning feature extraction and attention mechanisms in medical diagnosis. Both ResNet-50 and Inception-v3, when integrated with the SEOM module, enhanced the system's ability to prioritize informative features while suppressing less useful ones. The confusion matrices and accuracy plots revealed a high-performance level in classifying severity and predicting GCS scores. Importantly, the system's ability to incorporate multiple symptoms and clinical data types enhances its practical relevance in real-world healthcare scenarios, offering rapid and reliable assessment of brain trauma severity.

Overall, through the integration of SEOM modules, the attention mechanism further refined the feature maps by emphasizing the most critical channels, ultimately enhancing the model's ability to make precise and reliable predictions. The overall results indicate a consistently high accuracy, with ResNet+SEOM achieving 93% and Inception-v3+SE achieving 90%, reflecting a robust performance in differentiating various severity levels and key diagnostic features. This approach not only automates the feature extraction process but also ensures a more detailed and data-driven assessment of brain trauma, contributing to the advancement of machine learning applications in clinical support and medical decision-making.

Funding
This research was supported by the Tertiary Education Trust Fund (TETFund), Nigeria

Statement and Declaration
The authors declare no conflict of interest relating to this manuscript

REFERENCES

1. Abdullah, S., Siddique, A., Fatima, Z., & Shaukat, K. (2024). Traumatic brain injury structure detection using advanced wavelet transformation fusion algorithm with proposed CNN-ViT. *Information, 15*(10), 612. https://doi.org/10.3390/info15100612
2. Ajah, I. A., & Nweke, H. F. (2019). Big data and business analytics: Trends, platforms, success factors and applications. *Big Data and Cognitive Computing, 3*(2), 32. https://doi.org/10.3390/bdcc3020032
3. Albert, S., Wichtmann, B. D., Zhao, W., Maurer, A., Hesser, J., Attenberger, U. I., Schad, L. R., & Zöllner, F. G. (2023). Comparison of image normalization methods for multi-site deep learning. *Applied Sciences, 13*(15), 8923. https://doi.org/10.3390/app13158923
4. Alouani, A., & Elfouly, T. (2022). Traumatic brain injury (TBI) detection: Past, present, and future. *Biomedicines, 10*(10), 2472. https://doi.org/10.3390/biomedicines10102472
5. Bruschetta, R., Tartarisco, G., Lucca, L. F., Leto, E., Ursino, M., Tonin, P., Pioggia, G., & Cerasa, A. (2022). Predicting outcome of traumatic brain injury: Is machine learning the best way? *Biomedicines, 10*(3), 686. https://doi.org/10.3390/biomedicines10030686
6. Chae, J., & Kim, J. (2023). An investigation of transfer learning approaches to overcome limited labeled data in medical image analysis. *Applied Sciences, 13*(15), 8671. https://doi.org/10.3390/app13158671
7. Chandan, R., Vignesh, S., & Karpatne, A. (2020). *Predicting the effects of sedative infusion on acute traumatic brain injury patients* [Master's thesis, Virginia Polytechnic Institute and State University].

8. Chidi, E. U., Udanor, C. N., & Anoliefo, E. (2024). Exploring the depths of visual understanding: A comprehensive review on real-time object of interest detection techniques. *Preprints, 2024*, 2024020583. https://doi.org/10.20944/preprints202402.0583.v1
9. Covington, N. V., & Duff, M. C. (2021). Heterogeneity is a hallmark of traumatic brain injury, not a limitation: A new perspective on study design in rehabilitation research. *American Journal of Speech-Language Pathology, 30*(3), 974–985. https://doi.org/10.1044/2020_AJSLP-20-00081
10. Feigin, V. L., Vos, T., Nichols, E., Owolabi, M. O., Carroll, W. M., Dichgans, M., Deuschl, G., Parmar, P., Brainin, M., & Murray, C. (2020). The global burden of neurological disorders: Translating evidence into policy. *The Lancet Neurology, 19*(3), 255–265. https://doi.org/10.1016/S1474-4422(19)30411-9
11. Gu, C., & Lee, M. (2024). Deep transfer learning using real-world image features for medical image classification, with a case study on pneumonia X-ray images. *Bioengineering, 11*(4), 406. https://doi.org/10.3390/bioengineering11040406
12. Guan, B., Anderson, D. B., Chen, L., Feng, S., & Zhou, H. (2023). Global, regional and national burden of traumatic brain injury and spinal cord injury, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *BMJ Open, 13*(9), e075049. https://doi.org/10.1136/bmjopen-2023-075049
13. Guimarães, K., Amorim, R., Costa, M., & Costa, C. (2022). Predicting early traumatic brain injury mortality with 1D CNN and convolutional machine learning techniques. *Informatics in Medicine Unlocked, 31*, 100984. https://doi.org/10.1016/j.imu.2022.100984
14. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778).
15. Kekong, P. E., Ajah, I. A., & Ebere, U. C. (2019). Real time drowsy driver monitoring and detection system using deep learning based behavioural approach. *International Journal of Computer Sciences and Engineering, 7*(11), 11–21.
16. Khalili, H., Rismani, M., Nematollahi, M. A., Masoudi, M. S., Asadollahi, A., Taheri, R., Pourmontaseri, H., Valibeygi, A., Roshanzamir, M., Alizadehsani, R., Niakan, A., Andishgar, A., Islam, S. M. S., & Acharya, U. R. (2023). Prognosis prediction in traumatic brain injury patients using machine learning algorithms. *Scientific Reports, 13*(1), 960. https://doi.org/10.1038/s41598-023-28188-w
17. Malhotra, P., Gupta, S., Koundal, D., Zaguia, A., & Enbeyle, W. (2022). Deep neural networks for medical image segmentation. *Journal of Healthcare Engineering, 2022*, Article 9580991. https://doi.org/10.1155/2022/9580991
18. McDonald, B. Z., Tarudji, A. W., Zhang, H., Ryu, S., Eskridge, K. M., & Kievit, F. M. (2024). Traumatic brain injury heterogeneity affects cell death and autophagy. *Experimental Brain Research, 242*(6), 1645–1658. https://doi.org/10.1007/s00221-024-06856-1
19. Monteiro, M., Newcombe, V. F. J., Mathieu, F., Adatia, K., Kamnitsas, K., Ferrante, E., Das, T., Whitehouse, D., Rueckert, D., Menon, D. K., & Glocker, B. (2020). Multiclass semantic segmentation and quantification of traumatic brain injury lesions on head CT using deep learning: An algorithm development and multicentre validation study. *The Lancet Digital Health, 2*(7), e314–e322. https://doi.org/10.1016/S2589-7500(20)30085-6
20. Nag, M. K., Gupta, A., Hariharasudhan, A. S., Sadhu, A. K., Das, A., & Ghosh, N. (2021). Quantitative analysis of brain herniation from non-contrast CT images using deep learning. *Journal of Neuroscience Methods, 349*, 109033. https://doi.org/10.1016/j.jneumeth.2020.109033

21. Pease, M., Arefan, D., Barber, J., Yuh, E., Puccio, A., Hochberger, K., Nwachuku, E., Roy, S., Casillo, S., Temkin, N., Okonkwo, D. O., Wu, S., & TRACK-TBI Investigators. (2022). Outcome prediction in patients with severe traumatic brain injury using deep learning from head CT scans. *Radiology, 304*(2), 385–394. https://doi.org/10.1148/radiol.212181
22. Pierre, K., Turetsky, J., Raviprasad, A., Sadat Razavi, S. M., Mathelier, M., Patel, A., & Lucke-Wold, B. (2024). Machine learning in neuroimaging of traumatic brain injury: Current landscape, research gaps, and future directions. *Trauma Care, 4*(1), 31–43. https://doi.org/10.3390/traumacare4010004
23. Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., Siddiqui, T., & Mellit, A. (2023). A study of CNN and transfer learning in medical imaging: Advantages, challenges, future scope. *Sustainability, 15*(7), 5930. https://doi.org/10.3390/su15075930
24. Shamshad, F., Khan, S., Zamir, S. W., Khan, M. H., Hayat, M., Khan, F. S., & Fu, H. (2023). Transformers in medical imaging: A survey. *Medical Image Analysis, 88*, 102802. https://doi.org/10.1016/j.media.2023.102802
25. Tokareva, A., Starodubtseva, N., Frankevich, V., & Silachev, D. (2024). Minimizing cohort discrepancies: A comparative analysis of data normalization approaches in biomarker research. *Computation, 12*(7), 137. https://doi.org/10.3390/computation12070137
26. Xu, X., Li, Y., & Ding, X. (2024). Combined ResNet attention multi-head net (CRAMNet): A novel approach to fault diagnosis of rolling bearings using acoustic radiation signals and advanced deep learning techniques. *Applied Sciences, 14*(18), 8431. https://doi.org/10.3390/app14188431
27. Yan, J. L., Chen, Y. L., Chen, M. Y., Chen, B. A., Chang, J. X., Kao, C. C., Hsieh, M. C., Peng, Y. T., Huang, K. C., & Chen, P. Y. (2022). A robust, fully automatic detection method and calculation technique of midline shift in intracranial hemorrhage and its clinical application. *Diagnostics, 12*(3), 693. https://doi.org/10.3390/diagnostics12030693
28. Yazdan, S. A., Ahmad, R., Iqbal, N., Rizwan, A., Khan, A. N., & Kim, D. H. (2022). An efficient multi-scale convolutional neural network based multi-class brain MRI classification for SaMD. *Tomography, 8*(4), 1905–1927. https://doi.org/10.3390/tomography8040161
29. Zammit, C., Torzhenskaya, N., Ozarkar, P. D., & Calleja Agius, J. (2021). Neurological disorders vis-à-vis climate change. *Early Human Development, 155*, 105217. https://doi.org/10.1016/j.earlhumdev.2020.105217
30. Zhang, L., Bian, Y., Jiang, P., & Zhang, F. (2023). A transfer residual neural network based on ResNet-50 for detection of steel surface defects. *Applied Sciences, 13*(9), 5260. https://doi.org/10.3390/app13095260