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Leveraging Machine Learning for Enhanced Experience of Distance Learners

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Abstract
This study aims to determine the impacts of Machine Learning and Information Technology on e-Learning. Information technology has significantly impacted every aspect of human endeavours, including education. This research examined how machine learning can enhance users' experiences in distance learning. The dataset for the model was extracted from Kaggle, and training, testing, and evaluation were performed. The accuracy reached 60% due to the bias in the data distribution. Finally, the deployment of the model to monitor students' emotions in real-time, offering personalised content recommendations based on the detected emotional states, would enhance the user experience and facilitate a supportive learning environment by addressing negative emotions.

Keywords: Information Technology, User Experience, Machine Learning, E-Learning

Introduction

The component of educational services, digital technology being an essential part, has facilitated learning and improved pedagogy (Chengliang et al., 2024). As a result, there are now a variety of formal and informal learning environments that are different from traditional learning environments in terms of form, function, features, and patterns. The combination of education and technology provides a new approach to learning in the era of information and communication technologies (Mengchi & Dongmei, 2022). Learners can benefit from its convenience, accessibility, flexibility, and interactivity at any time and location. It allows them to stay up to date on current events, look for study solutions, and improve their experience and knowledge through relevant interventions, study design, and prompt response (Dewan et al., 2019). The rapid growth and widespread use of e-learning platforms have fundamentally changed how students are taught educational materials (Mengchi & Dongmei, 2022). Students learn by being actively engaged in relevant and authentic activities, which are interactive, which technology has made possible (Freeman, 2014). E-learning is the use of information and communication technology to enhance learning quality by providing remote collaboration and exchange, as well as access to resources and services. Because of its advantages, steady expansion, and the pervasiveness of computers, cellphones, and other electronic devices, e-learning can help students succeed. In Nigeria, different learning management systems (LMS) are being used in different Universities to facilitate distance learning, and there is a need to improve the users' experiences in using the systems for greater results. The user experience (UX) takes precedence while building an LMS product because it affects how users interact and perceive the learning platform. User experience (UX) design is a crucial component of eLearning. While poorly designed UX might cause learners to become frustrated and give up on the learning platform, well-designed UX can increase learners' engagement and happiness. Good UX design in eLearning has several important advantages, such as better learning outcomes, higher retention, enhanced accessibility, and increased efficiency. Teachers may develop an e- learning experience that is engaging and available to all students. User experience frequently focuses on the product's value and how users perceive it to meet organisational objectives. Although there are many different methods to think about and incorporate user experience into interactive product design, usability, functionality, aesthetics, content, look and feel, and emotional and sensory appeal are all crucial. (Rogers et al., 2011). Maintaining effective UX design requires constant feedback collection, as well as updates and platform enhancements based on that input. Another major cause for the change in the emotions of the students during learning is their experience with the system. The users must be factored into the design of the learning management system.

According to Al-Sa'di et al. (2014), maximising the user experience (UX) is crucial for dynamically changing the design in response to the user's emotional responses when interacting with the system. To do this, it is essential to identify the feelings, experiences, and abilities of users as well as the areas that need improvement. For this reason, assessing users' feelings, experiences, and abilities as well as identifying the areas that need improvement are essential. Traditionally, Humans analyse and process data, but the large amount of data available that needs to be put in context and in an organised form to be able to understand it has brought about computer systems that can imitate them. They are known as machine learning, and they use both data and data changes to solve issues. Previously, approaches to face recognition employed static photos and a face dataset to identify one or more faces in a scenario. Due to recent improvements in camera performance and technological cost reductions, face recognition is now widely used in video surveillance, games, mobile payments, and many other industries. Because of this, a lot of video data is produced, and there is a need to process it.

One of the technologies that is expanding the fastest right now is machine learning (ML), which has many industrial fields and prototype applications. The technology's promise has been revealed in a variety of fields, including robotics, computer vision, manufacturing, medical, knowledge acquisition, execution and control, design, planning, and scheduling. Research utilising networks and new media has also revealed a need for machine learning in information retrieval and navigation (Vassilis and Juergen 2010). Research, teaching, learning, and education are all being drastically changed by machine learning. This innovative approach aims to accelerate the educational system's progress. Machine learning, especially in the teaching and learning domains, is one of the best illustrations of how technology improves human processes. Researchers are accelerating research with its use to unlock discoveries and insights. It is expanding the reach and impact of online learning content through localisation, transcription, text-to-speech, and personalisation (Amazon Web Services, 2023). E-learning frameworks can be improved by machine learning, which not only cleverly learns existing projects but also adds the ability to place students in these learning frameworks (Mohri, 2012). Machine Learning is critical to accomplishing enhanced E-learning frameworks. As a technique for enhancing e-learning frameworks and strategies, it is related to information mining. It supports methodical adaptation and helpful realisation, which can effectively manage clients through purposeful requests and search. Given this ability, it performs better than static learning materials in terms of answering questions concerning equipment. Then again, the Learning Management System (LMS) supports productive learning. In spite of the fact that the usefulness of a subject guide is predictable and deliberate, it is also achievable for project-based learning. There are different kinds of machine learning models, but to achieve face recognition and emotions of the students/learners, a convolutional neural network has been used, which achieved some results. The field of deep learning has rapidly expanded and been effectively applied to a wide range of conventional applications. More importantly, DL has outperformed well-known machine learning algorithms in a variety of fields, such as education, cybersecurity, bioinformatics, medical information processing, natural language processing, robotics and control, and many more. (Taye, 2023).

The field of machine learning has grown from a small group of computer engineers who wanted to know if computers could learn to play games to a broad field that has created basic statistical-computational theories of learning processes, created learning algorithms that are used extensively in commercial systems for speech recognition, computer vision, and many other tasks, and given rise to a data mining industry that looks for hidden patterns in the vast amounts of online data (Tom, 2020). This is an area of study that aims to provide a solution to the question, "How can we create computer systems that will learn and get better on their own with experience" (Sharma, 2024)? Giving a computer any task involves either implementing an algorithm that outlines the rules that must be followed or providing a set of precise instructions, because computer system lacks the capacity to learn from the past, it is unable to quickly make improvements based on past errors (Zarsky, 2016). Therefore, defining a thorough and accurate algorithm for a task and programming it into the computer are necessary before assigning a computer or computer-controlled programme to do it. Machine learning, though it has become a household name among the computing community and has enjoyed huge success in recent years, is a method of achieving artificial intelligence. It is an area of computer science and artificial intelligence (AI) that focuses on using data and algorithms to mimic human learning processes while progressively increasing their accuracy. It is a collection of techniques that, in general, "teach" computers how to do things by giving them examples of the proper way to do them; it also teaches a computer system how to make accurate predictions when fed data. The primary distinction from conventional computer software is that the code that tells the

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system how to distinguish between an apple and a banana was not created by a human developer. Rather, a machine-learning model has been trained on a vast amount of data, most likely a vast number of images labelled as including an apple or a banana, to teach it how to consistently distinguish between the fruits. Machine learning concentrates on a set of methods within Artificial intelligence that are predicated on "learning" to model patterns in data using mathematical functions. Since a substantial portion of machine learning's mathematical foundation is derived from traditional statistics, the field is also referred to as "statistical learning" (Rattan *et al*, 2022). Machine learning departs from classical statistics by utilising its roots in computer science to leverage higher-dimensional mathematical operations on considerably bigger data sets to interpret intricate, nonlinear relationships.

Using Haar-like features, Jung et al. (2015) seek to use deep learning techniques to identify face expressions that reflect human emotions. Their facial expression recognition system functions as follows: First, the face in the input image is identified using Haar-like features. Second, the deep network is used to identify facial emotions using faces that have been found. At this level, two different deep networks, such as the deep neural network and the convolutional neural network, can be used. Consequently, the convolutional neural network outperformed the deep neural network in our experimental comparison of the two types of deep networks. A study by Ruiz et al. (2018) investigated a system that can recognise emotions in human facial expressions and instantly apply that knowledge to a robot. They introduced a novel hybrid deep learning emotion identification model, building on previous research, and showed initial findings on the real-time emotion recognition of our humanoid robot. A Deep Convolutional Neural Network (CNN) is utilised for self-learned feature extraction, while a Support Vector Machine (SVM) is employed for emotion classification. This hybrid deep learning model achieves a state-of-the-art classification rate of 96.26 percent on the Karolinska Directed Emotional Faces dataset, outperforming more complex approaches that use more layers in the convolutional model. Tested on the Extended Cohn-Kanade dataset, it performs comparably on unknown data. We offer a collection of emotion identification models that were used on the KDEF dataset for both training and testing. On the KDEF dataset, our best model—which combined CNN and SVM—achieved state-of-the-art performance rates, and on the CK+ dataset, it produced results that were on par with larger models. Nevertheless, the results of our hybrid CNN+SVM design fell 3 points, or 73%, short of the state-of-the-art. When tested on the CK+ dataset, it should be mentioned that the CNN component of the model was not trained using any of the CK+ images. In spite of this, our hybrid model has fewer model parameters, converges more quickly, and requires less data to train.

Liu et al. (2016) provided a framework and design guide for developing an intelligent system that can recognise emotions in MOOC courses through personalised and sensitive analysis. Their approach to enhancing MOOCs is predicated on multi-attribute decision-making and text mining. First, we look through student comments to identify course features that they are interested in using word vectors and clustering methods. Second, we use certain BERT-based deep learning algorithms to do a sentiment analysis on these comments to determine learners' emotional dispositions toward course elements and non-emotional information. Finally, by carefully weighing the attention, emotional score, non-emotional content, and improvement costs of the attributes, we use the multi-attribute decision-making technique TOPSIS to give course designers a priority ranking for attribute improvement. This method was applied to two popular MOOC programs. Our method's ability to extract course attributes from reviews, assess learners' attention, contentment, and cost of improvement, and then generate a prioritised list of course attributes that require improvement is demonstrated by the experimental results. This study promotes the long-term improvement of the quality of online education and presents a novel approach to improving its standards. Gupta *et al* (2018) proposed a new method for face recognition instead of providing and using the initial pixel values as input. Facial features are provided and used to shorten the time and reduce complexity. Deep networks of the Convolutional Neural Networks (ConvNets) kind have been shown to function well for FR. Their study suggests a novel method for face identification utilising deep neural networks, another kind of deep network. In this method, raw pixel values are not provided. The Yaleface database, which has 165 black and white photos altogether from 15 samples—each with 11 images in various expressions—is used to test the suggested strategy. They provide pictures of the same figure with various facial expressions or configurations: happy, sad, sleeping, astonished, winking, normal, left-light, happy with glasses, and left-light without spectacles. There are a total of fifteen classes because the categories are specified as subjects plus labels. There are two sections to the entire dataset: 148 photos for training and 17 images for testing. At the softmax layer, the final average accuracy is determined by counting the number of test samples that were successfully identified. The frontal face feature of the Haar Cascade is used for pre-processing using the OpenCV library. Python packages keras, theano, and tensorflow are used in the creation and training of neural networks. The suggested system's final average accuracy of 97.05% is about 97.5%, which is comparable to human facial recognition accuracy. The concept is applied to a 64-bit Python 3.5.3 system. Because there are fewer redundant input features when facial features are extracted and fed using Haar cascade rather than raw pixel values, the complexity of neural network-based recognition frameworks is reduced. Additionally, utilising DNN rather than ConvNets speeds up and lightens the procedure.

Hazarika et al. (2018) researched Multimodal Emotion Detection using Self-Attentive Feature-level Fusion. Finding speech-level emotions in two-way conversation footage is the aim of the project, which will help researchers choose the best fusion process and promote the application of our proposed fusion technique in future multimodal systems. A multimedia approach comprising textual, audio, and visual components makes up the system. Ten speakers, five of whom were male and five of whom were female, engaged in two-way dyadic conversations in the multimodal dataset IEMOCAP2. The conversational videos are then divided into smaller utterance videos by segmenting them into individual utterances. One of the following emotion tags is applied to each utterance: neutral, happiness, sadness, or anger. In order to prevent speaker overlap between the training and testing sets, we use the first eight speakers' conversations as the training fold and the remaining ones as the testing fold. The advantages of our suggested attention scheme for feature-level fusion are also supported by the results and comparative analysis, which demonstrate the capabilities of various fusion techniques. The multi-dimensional attention module was found to perform best for fusion in a noise stability test that they also conducted.

A generalisation of the neural cognitive machine is the convolutional neural network. Convolutional neural networks are multilayer networks used for training that are made up of several single-layer convolutional neural networks (Zhang and Jing, 2023). Nonlinear transformation, down-sampling, and convolution are all included in a single-layer convolutional neural network. Every layer has a feature map as its input and output, made up of a collection of vectors (the first layer's initial input signal can be thought of as a high-dimensional feature map with high sparsity). This research aims to ascertain the gains that information technology and machine learning have brought to distance learning. The emotions and state of mind of the learners need to be captured to determine the best way of lecture delivery. Machine learning has played a significant role in making predictions that have helped e-learning (Ojajuni et al., 2021) and has led to dynamic adaptability, which fosters a supportive and interactive learning atmosphere, ensuring that users' feelings are understood and valued.

Aim and Objectives of the Study:
This research aims to investigate the impact of information technology and machine learning on distance learning, with a focus on capturing learners' emotions and state of mind to determine the most effective lecture delivery methods. The objectives are to:

1. examine the role of machine learning in predicting learner needs and fostering a supportive and interactive learning atmosphere.
2. develop a system that uses facial expression recognition to determine learners' emotional states and adjust the learning content accordingly.
3. identify potential learning difficulties through machine learning-based analysis of negative emotion patterns.
4. create personalized learning experiences that adapt to individual learners' needs and emotions.
5. investigate the impact of machine learning-based interventions on learner engagement and motivation.

Methodology

Methodology is a setup of a detailed and structured process to be followed across the stages of the system development life cycle by the developers. Methodology is a formalised approach to implementing the System Development Life Cycle (SDLC). In this research, Structured System Analysis was adopted for developing and implementing a model designed to detect the facial expressions of learners and therefore detect their emotions while in an online learning environment. It provides a detailed explanation of the proposed model design, data collection, preprocessing techniques, model architecture, training process, and evaluation metrics employed in this study.

Research Design and Data Collection: It involves experimentation and analysis of acquired datasets. The research predominantly employs a quantitative research approach. The quantitative method involves the generation of numerical data. It is used for systematic and rigorous quantitative analysis. The dataset used for training, evaluating and validating the model was obtained from Kaggle. This dataset was specifically curated for facial emotion recognition tasks. There are 28,079 grayscale photos with a 48x48 pixel resolution in the Training Set. To guarantee that the face is in the centre of each picture and takes up a constant amount of space, these photos are cropped and aligned. Consistency between the two sets and a precise assessment of the model's performance are made possible by the 7,178 photos in the testing set having the same dimensions and pre-processing as the training set, as displayed in Figure 1 below.

Figure 1: Data Collection distribution

Existing System

A study on the Conceptual Model for Developing E-Learning Systems Based on User Learning Patterns and Styles was carried out by Aniedu et al. (2018). According to their perspective, learning platforms are made up of three main components: the content authoring system, which creates courses and course modules and manages the system's assessment; the content management system, which manages the system's coordination and administration; and the content management system, which serves as the meeting place for facilitators and students during learning processes. The block diagram of a typical learning process platform is displayed in Figure 2

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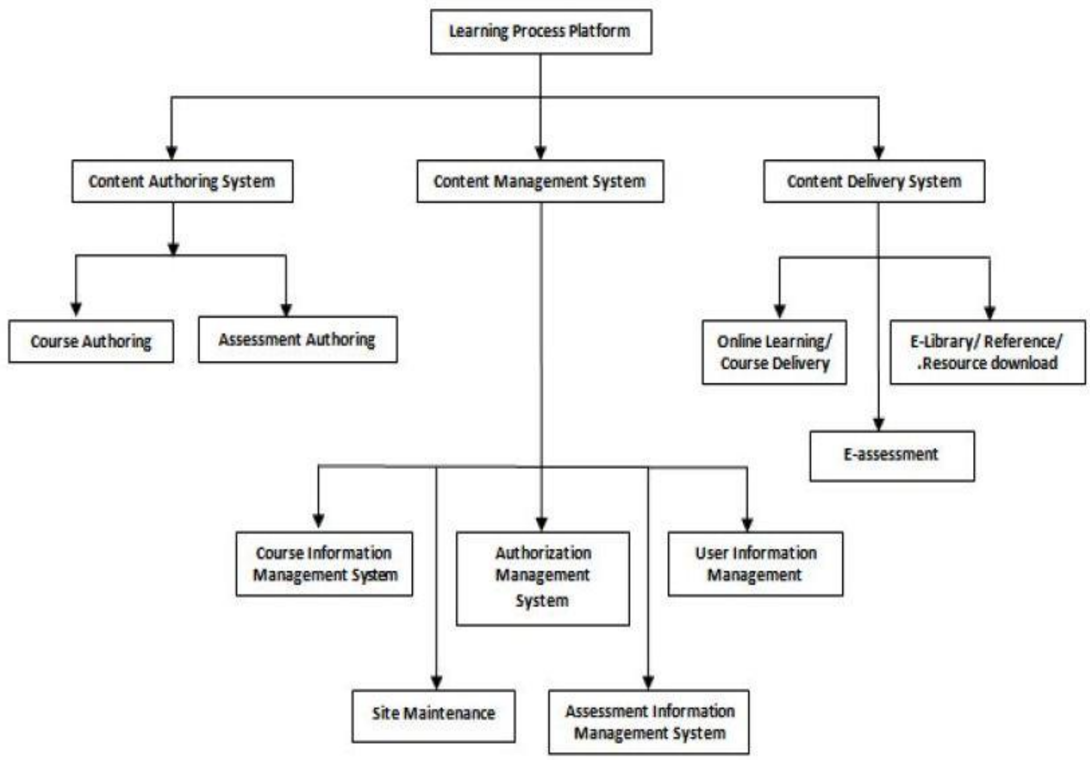

Figure 2: Block Diagram of the existing system. Source: (Aniedu et al., 2018)

Machine Learning Model

The model, a conceptual ensemble learning architecture integrating ResNet, VGG16, and custom CNN, will detect in real-time facial expressions and classify the emotions of learners as either surprise, anger, happiness, sadness, neutral, and fear and therefore make recommendations to the learners. The model will be added to the content delivery aspect of the learning management system as shown in the diagram below.

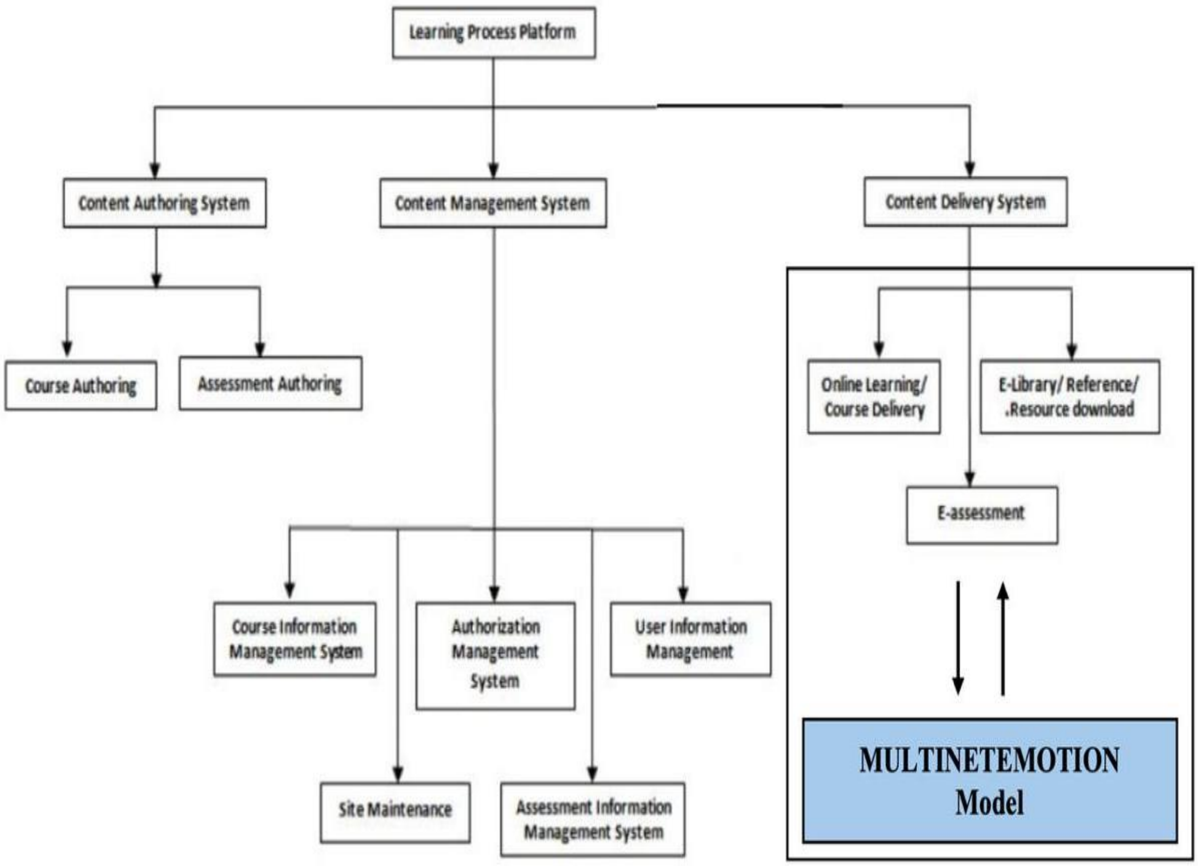

Figure 3: Machine learning Model

The Model
The diagrams show the techniques applied to the dataset to develop a machine learning model.

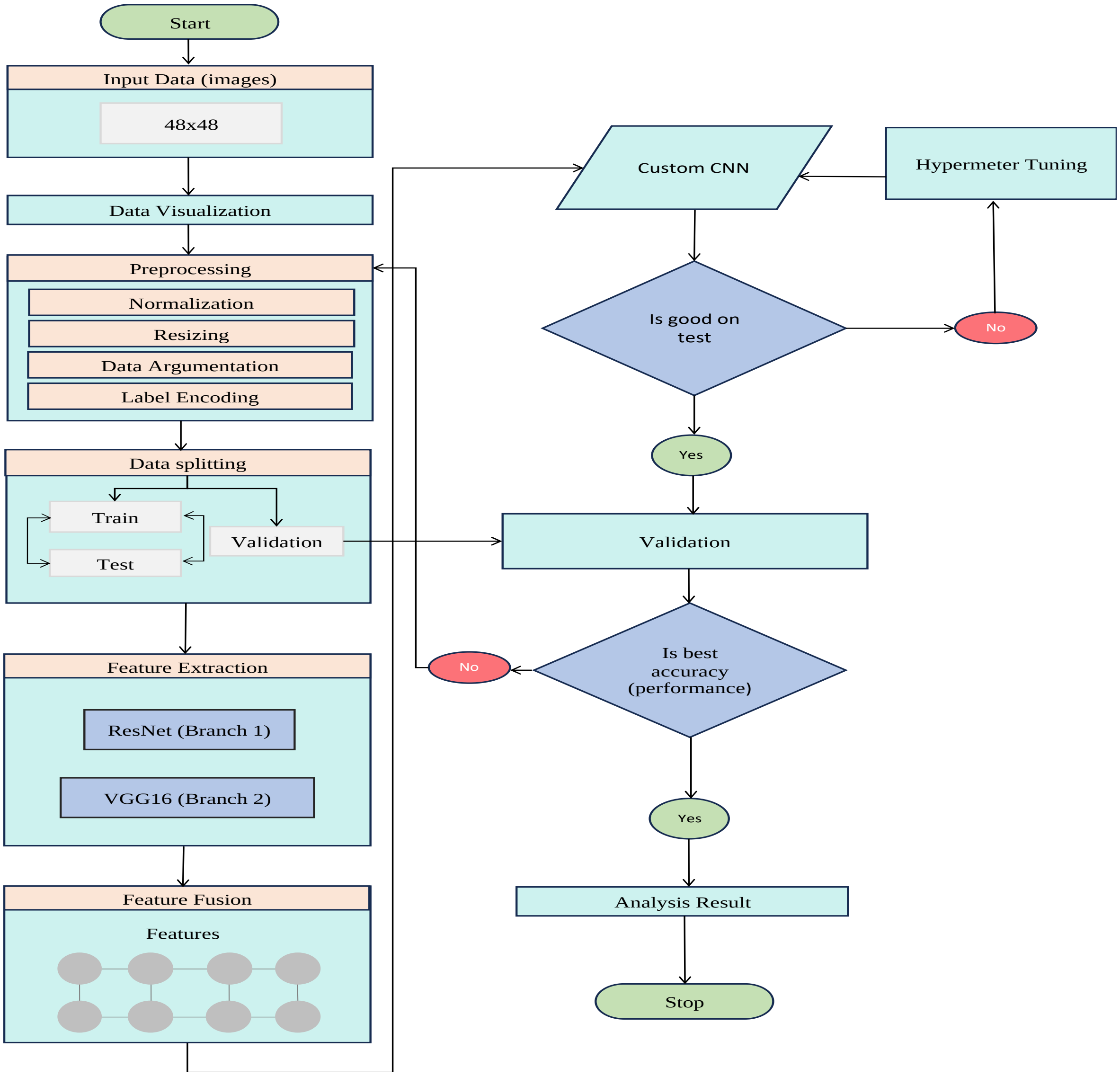

Figure 4: Flowchart of the Model process

Preprocessing Techniques

To ensure optimal performance of the model, a series of preprocessing techniques were applied to the dataset before feeding the data into the model. Preprocessing is a critical step in machine learning workflows, particularly in deep learning, as it enhances the quality of the data and reduces potential biases that could affect model performance. The following preprocessing techniques were employed:

Grayscale Image Normalisation

As the dataset consists of 48x48 pixel grayscale images, the pixel intensity values, which range from 0 to 255, were normalised to a scale between 0 and 1. This normalisation helps the model converge faster during training by ensuring that the input values are in a similar range. Normalising the pixel values also helps reduce the risk of large gradient updates, thereby stabilising the learning process. The formula for normalisation is shown in equation 1.

$$X_{\text{normalized}} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{equation (1)}$$

where $X_{min} = 0$ and $X_{max} = 255$.

Image Resizing
Although the dataset images are already 48x48 pixels, this resolution was preserved for all images during preprocessing. This resolution is small enough to reduce computational complexity but large enough to retain important facial features required for emotion recognition. By keeping the images at a uniform size, the model can process the data efficiently without the need for additional resizing during training.

Data Augmentation
On the training set, a number of data augmentation approaches were used to avoid overfitting and enhance the model's generalisation. The model can learn robust characteristics even under different situations thanks to these augmentations, which produce somewhat different versions of the original images. The following additions were made. Random Horizontal Flip: Randomly flipping the images horizontally to simulate natural variations in facial orientation. This helps the model generalise better to real-world scenarios where facial orientation may differ.

- Random Rotation: Applying small random rotations to the images (e.g., between -10 and +10 degrees) to introduce variability in the dataset. This helps the model learn rotationally invariant features.

- Zoom and Shift Transformations: Small random zooms and shifts were applied to simulate different distances from the camera and slight variations in facial position. This aids the model in learning to detect emotions even when the face is not perfectly centred or scaled.

These augmentations were only applied to the training set to avoid introducing artificial variability into the testing set, which is reserved for unbiased model evaluation.

Label Encoding
Since the dataset consists of categorical labels representing the seven emotional expressions (Surprise, Anger, Happiness, Sadness, Neutral, Disgust, Fear), these labels were converted into numerical form using one-hot encoding. This transformation is necessary for multi-class classification problems like facial emotion detection, as it allows the model to interpret the labels as distinct categories rather than ordinal data.

For example, the emotion label "Happiness" is represented as:

Happiness→[0,0,0,1,0,0,0] Happiness→[0,0,0,1,0,0,0]

Data Splitting

Although the dataset is already divided into training and testing sets, the training set was used to build an additional validation set. To track the model's performance throughout training and avoid overfitting, a small portion of the training data—say, 10–20%—was reserved as a validation set. This guarantees that the model is effectively generalising to new data and not only learning the training set.

Batch Processing
For efficient training, the images were processed in batches. Batch processing not only speeds up the training process but also stabilises gradient updates by averaging the gradients over multiple samples. A batch size of 32 or 64 was used based on the memory and computational constraints, ensuring that the model trains efficiently without overloading system resources.

Conclusion
The Model was extensively evaluated, focusing on both the training and testing stages of the model. Initially, the model's architecture and parameter configuration were explored, highlighting the significant steps taken to optimise performance. Various hyperparameters such as batch size, learning rate, and dropout rate were tuned to ensure optimal training outcomes. The evaluation metrics, including accuracy, loss, precision, recall, and F1-score, were presented, showcasing the effectiveness of the model in classifying emotions across six categories: Angry, Fear, Happy, Neutral,

Sad, and Surprise. The model's training performance improved over the epochs, but signs of overfitting emerged as the validation loss increased despite improving training accuracy. Furthermore, a comprehensive analysis of the confusion matrix revealed the model's strengths and weaknesses in classifying different emotions, with the best performance observed in recognising Happy and Surprise emotions and the most challenges with Fear and Sad. The validation accuracy reached 60%, which, while promising, indicates room for improvement. Finally, the deployment of the model to monitor students' emotions in real-time, offering personalised content recommendations based on the detected emotional states, would enhance the user experience and facilitate a supportive learning environment by addressing negative emotions.

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