**Machine Learning Group Assessment (KV7006)**

Facial Emotion Recognition

**Group ID 25, Word Count - 2500**

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| --- | --- | --- | --- | --- |
| *Arka Mandol* | *Ifeoma* | *Lilian* | *Sai Dheeraj* | *Nkemjika* |
| *W23023023* | *W23057234* | *W23030767* | *W23023865* | *W22055838* |
| *Data Science* | *Data Science* | *Data Science* | *Data Science* | *Data Science* |
|  |  |  |  |  |

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# Introduction

Facial Emotion Recognition (FER) is a vital aspect of machine learning and artificial intelligence, which identifies and classifies human emotions from facial expressions in images or videos with widespread application in security, psychology, medicine, virtual reality, human computer interaction and more (Canedo & Neves, 2019). Different algorithms have been helpful in the growth of this domain offering distinctive features and methods. CNN (Convolutional Neural Networks) process grid-patterned data, particularly images by learning and improving spatial hierarchies which akin to animal visual systems. Fuzzy logic accommodates uncertainties, complementing traditional logic and enabling human-like reasoning in complex systems (Zadeh, 1965; Mendel, 2001). The Long Short-Term Memory (LSTM) network, a potent tool in Recurrent Neural Network (RNNs), effectively manage extended dependencies in sequence prediction tasks (Greff et al., 2017). Support Vector Machines (SVMs) bridge the gap in human-computer interaction, particularly in facial emotion recognition by creating FER systems in the context of face emotion recognition (Dagher et al., 2019). Deep Belief Networks (DBNs) classify images, improving emotion identification skills by hierarchically learning features and correctly classifying facial expressions (Dahshan et al., 2020).

## Selected Literature

One research paper standout for thorough coverage and relevance to our research "A Survey on Facial Emotional Recognition techniques: A State-of-art literature review.” This paper provides and in-depth review of many aspects of FER including algorithms, datasets, methodology, computational flow, preprocessing, feature extraction, etc. providing invaluable resource for comprehending FER intricacies.

## Machine Learning Task Formulation

For this task we explored literature on facial emotion recognition that properly recognize different facial expressions. Our task is a classical machine learning problem with picture inputs of face and output of a label showing the emotion expressed by the face. The steps involved in carrying out the task in literatures explored are pre-processing, face detection, conversion, feature extraction and so on. Challenges like lighting, obstructions, surroundings, and random emotional display that vary based on cultural differences which result in increased computing cost, learning time, and degrade model performance (Mohana et al., 2023).

## Datasets

The datasets used in this research papers are mainly JAFFE (Japanese Female Facial Expression), FER2013, and CK+ where each of them serves as essential reference points for assessing algorithm performance across emotional and demographic circumstances.

# Methods and Analysis

## Data Preprocessing

Preprocessing is a crucial step in the Facial Emotion Recognition (FER) domain as it helps refine input data for model training (Kopalidis et al., 2024). Going by the literatures we reviewed, similar preprocessing steps are shared between Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs), with an emphasis on data conversion, face detection, augmentation, scaling, and normalization to assure consistency and improve data variety.

### Data conversion

This step converts unprocessed raw data such as images or videos into a suitable format for analysis. Images can be resized, video frames can be divided, or images can be converted to common colour schemes like RGB or grayscale. Maintaining consistency in formatting makes preprocessing and analysis easier later.

### Face Detection

Facial expression recognition starts with face detection, which is the first step towards facial expression identification. This technique is essential for identifying the Region of Interest (ROI) in an input image, which is further developed in the facial expression recognition (FER) system's subsequent phases. A common method for face recognition is the Viola-Jones face detection algorithm (Ballesteros et al., 2024). After analysing a large number of photographs, the algorithm learns to recognize particular patterns in the images known as Haar features, which allow it to distinguish between faces and other things. Over time, the system improves its ability to detect objects in images by learning from its mistakes. By combining several weak classifiers into one strong classifier, the adaboost classifier is frequently used to improve the viola-jones face identification algorithm's performance (Kopalidis et al., 2024).

### Normalization and Augmentation

This step ensures uniform data representation by scaling pixel values to a specified range. While augmentation increases data diversity using changes like rotation or flipping, resizing standardizes image dimensions to enable uniform processing.

LSTM models use unique preprocessing techniques designed for sequential data. On other hand Standardization and scaling are given top priority by support vector machines (SVMs) to guarantee feature comparability and model performance.

Fuzzification is a special kind of preprocessing that makes fuzzy logic stand out. By converting exact numerical values into fuzzy sets, a process known as "fuzzification," real-world data's complexity and uncertainty are efficiently accommodated. (Klir & Yuan, 1995)

## Feature Extraction

Feature extraction is a crucial step in FER (Kopalidis et al., 2024). To find facial expressions from frontal photographs, it is important to extract from the image a collection of primary parameters that best characterize the specific set of expressions so that the parameters may be used to differentiate between expressions. The amount of information retrieved from the image to the feature vector is the single most crucial component of a successful feature extraction technique. This set of parameters is known as the image's feature vector. If the feature vector (Bashyal & Venayagamoorthy, 2008)

## Machine Learning Models and Algorithms

### Hierarchical Deep Belief Network (DBN)

DBN classifiers adopt Reduced Boltzmann Machines in its structure to establish connections between different layers of neurons which are the visible (input layer) and the hidden (latent variable) units. To train this model, the Contrastive Divergence methodology is applied. Using this approach the network is trained layer by layer ensuring that each layer can continuously identify complex patterns from the input data (Dahshan et al., 2020). While the input data is processed through the network, additional information is extracted by each layer. This method of hierarchical feature extraction allows the network to understand complex features in the images. Hence, for subsequent testing, the Deep Belief Network utilizes its acquired knowledge to generate output responses.

### Fuzzy Logic

By considering uncertainty between "true" and "false," fuzzy logic goes beyond conventional Boolean logic and allows for better comprehension and understanding of complex and uncertain data (Klir & Yuan, 1995). According to Ross (2010) the Fuzzy technique identifies features in a dataset that experience discrepancies and uncertainties for better understanding and processing. Mamdani and Sugeno models are examples of fuzzy inference systems that use data analysis or expert knowledge to infer rules. Sugeno models use mathematical functions to produce more accurate results, while Mamdani models use linguistic variables and fuzzy sets to capture qualitative characteristics (Mamdani & Assilian, 1975; Takagi & Sugeno, 1985). Due to its adaptability, fuzzy logic can be used in a wide range of situations where uncertainty is present, such as control systems and artificial intelligence.

Convolutional Neural Networks (CNNs)   
CNNs is frequently used for processing grid patterned images with its main aim to automatically and continuously learn spatial hierarchies of features ranging from low to high level patterns (Yamashita et al., 2018). They also imply that its ability to anticipate local face features and adopt multitask deep learning has made it possible to recognize a wide range of facial expressions.   
CNNs is made up of convolutional, pooling, and fully linked layers. The convolutional layers use convolutions to extract features from the input data by application of filters after which the feature maps acquired are subsequently down sampled by the pooling layers, which lowers computing complexity while maintaining crucial information. Once this process is concluded, fully connected layers categorize the input data into distinct groups based on the attributes retrieved.

### Long Short-Term Memory (LSTM)

According to Greff et al., (2017), LSTM models are specialized recurrent neural network architectures known for their ability to incorporate long-term dependencies within sequential data. LSTM models consist of feedback connections that enable it to process an entire data sequence which is made up of a storage unit and three control gates which include input, forgetting and output gates (Guo & Chen, 2020). The storage unit of the LSTM model well known as the cell state plays a crucial role in the retention of the input data integrity (Landi et al., 2021). This model demonstrates a distinctive ability to analyse entire sequences of data while fussily keeping or discarding information.

Support Vector Machines (SVMs)   
SVMs utilises a three-step feature classification method, using different SVMs for various binary expression combinations. By finding the best hyperplanes to divide several classes in the feature space, SVMs are very good at categorizing complicated datasets (Dagher et al., 2019). Because SVMs can handle high-dimensional data and generalize well, they are frequently used in facial emotion recognition. Their proficiency in binary and multi-class classification problems renders them adaptable to a broad spectrum of pattern recognition and machine learning applications. Because SVMs can detect minute variations in high-dimensional feature spaces, they are essential for correctly classifying face expressions in FER.

## Training and Validation

The dataset is partitioned into training, validation, and testing sets for our five models previously described. The training set is utilized for iterative optimization throughout training, and performance is monitored on the validation set. The five models' performance is assessed on the validation set using standard metrics like accuracy, precision, recall, and F1-score.

# Discussion & Evaluation

## Results Summary

The researchers are using many different techniques of many different machine learning model to increase their performance and accuracy for example the k-flod technique is used for CNN to reach the validation accuracy of 85%on the FER-2013 dataset and 81% accuracy on the ck+ datasets while coming to the facial emotion detection Applications where precision is paramount, such as security and human-computer interaction, are well-suited to CNNs (Appasaheb Borgalli & Surve, 2022).

There are two fundamental areas in the fuzzy logic models one is superior accuracy and the second is the adaptability in the field of medical diagnostics and control systems (Ross, 2010; Mamdani & Assilian, 1975).

The SVMs can provide reliable information by identifying the facial emotions on their faces with an accuracy level of 99.72% and 98.10% respectively to the JAFFE and RaFD datasets and around 90% across many other datasets and these are prominent features used in public safety and interactive media (Dagher et al., 2019).

The temporal data should be handled more consistently and efficiently, so the LSTM network is the best tool for sequential prediction problems. Healthcare monitoring is one of the best applications that rely on long data sequences for these datasets the accuracy and timely predictions greatly impact patient outcomes (He et al., 2020).

The DBNs are unrivaled in accuracy and efficiency when it comes to the processing of the timeframes with a reduction percentage of 62% and 82% with the JAFFE AND FER-2013 dataset. This proves that the DBNs can expedite data processing without compromising precision. This also proves that the DBNs might be useful in real-time applications as well where the processing speed is paramount (Eldahshan et al., 2020).

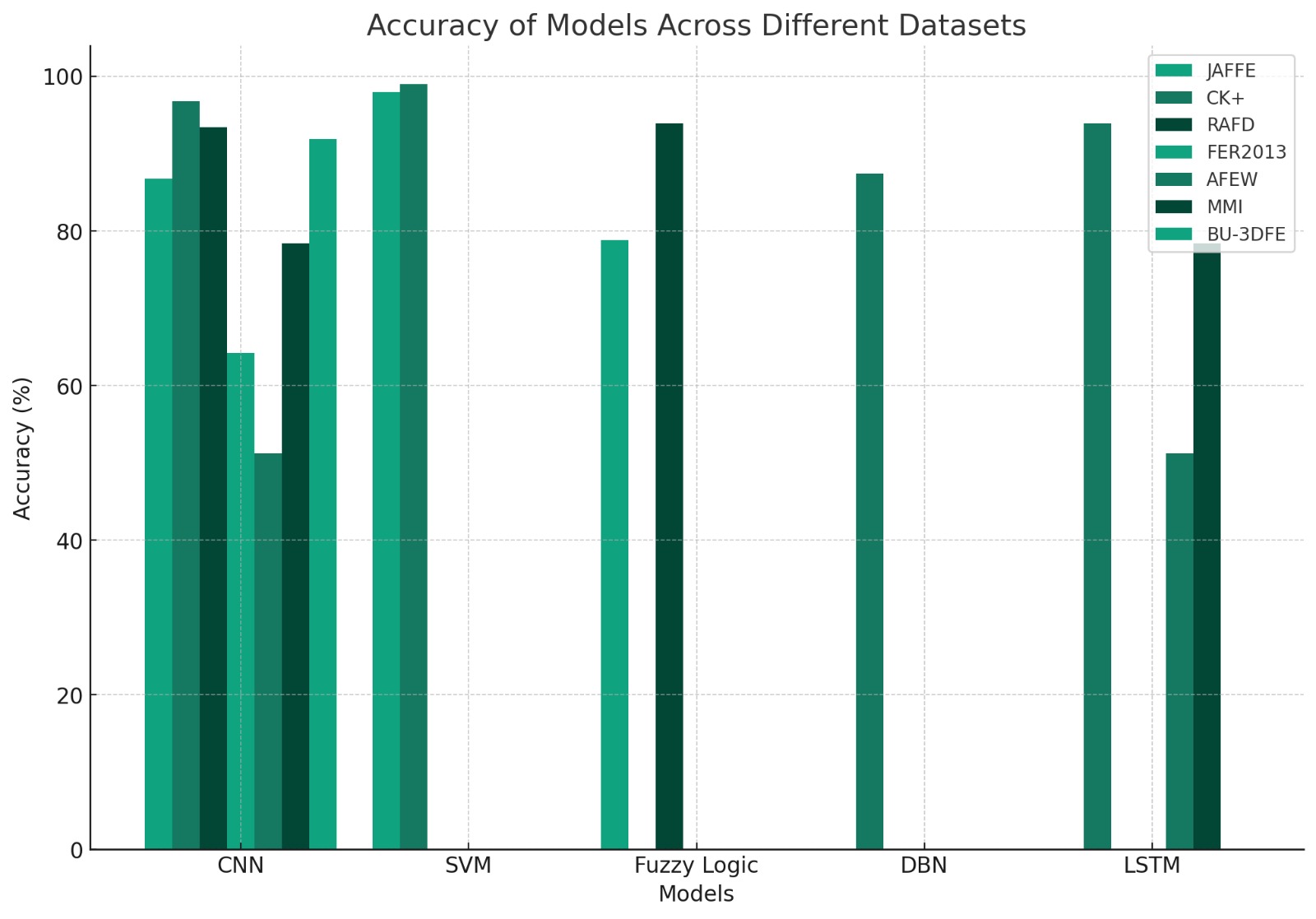
## Comparative Analysis

The pros and cons of any machine learning model can be tested only by comparing and evaluating their performance on a challenging dataset with specific tasks. CNNs excels in one area of proficiency, that is processing image data. With finding the patterns and feature extraction from the images are main area it excels these are the key feature for the face recognition applications and with the end to end learning and automated feature extraction shows its strength rather than the traditional once (Shao & Qian, 2019).

Fuzzy logic model stands out from the other models due to its unique approach to the problem solving with capacity to emulate human cognition and handling the ambiguity to the problem-solving approach which makes it to stand out from the other neural networking models (Zadeh, 1996; Lin & Lee, 1996).

When it comes to the extracting of the facial subtle feature the SVM outperforms any older machine learning and mewer deep learning models the contrast shows how accurate and resilient the SVM models (Bhadangkar & Pujari, 2020; Hanin, 2023).

The gain is the important thing to be consider when dealing with the time series data or the data that is highly dependent on time such as speech recognition and predictive typing systems the LSTM network consists of sequential processing input which is more suitable for these kinds of data rather than the Traditional Recurrent Neural Networks (RNNs) (Mohana et al., 2023).



## Systematic Critique

CNN models are effective but while handling images data, the image quality differ their efficiency and these provide a systematic assessment of these studies reveals range of issues and potential solutions using different machine learning models (Shao & Qian, 2019)

Fuzzy logic has more benefits with very few issues, by choosing the correct membership function and rule set the model performance and readability are impacted but many people think it is a researching issue. (Klir &Yuan,1995; Mendel 2001)

Whenever the support vector machine is exhibited to the significant bias model it often fails to provide satisfactory results while coming to the classification tasks it has exceedingly high accuracy rate to overcome this there are more sophisticated sampling techniques or algorithmic adjustments are required (Batuwita & Palade, 2013).

Even the LSTM network also has limitations when it comes to the long data sequences. They typically fail to capture the long-term dependencies due to the vanishing and exploding gradients; hence, attention models and similar processes are necessary to improve their performance (Mohana et al., 2023).

# Conclusion

The working of machine learning algorithms in Facial Emotion Recognition (FER) has been demonstrated in the literature review carried till now. These algorithms have been used in a number of fields, such as security and healthcare. CNNs are well equipped for quick and dependable real-time FER applications since they have demonstrated flawless precision and proficiency in visual input analysis (Yamashita et al., 2018). SVMs have shown proven to be highly effective in multi-class classification, an essential task for precise emotion identification (Dagher et al., 2019). Furthermore, LSTMs have shown usefulness in managing temporal data, especially in sequence comprehension for predictions related to healthcare monitoring (He et al., 2020). Fuzzy logic is integrated to help manage uncertainty and simulate human reasoning by adding complexity to decision-making processes. When binary logic is not enough this flexibility enables development systems to run correctly (Mamdani & Assilian, 1975; Matthews & Ross, 2010). DBN's increased real-time likelihood capacity, which come from processing efficient data and learning hierarchically, are important for applications that require quick responses (Dashan et al., 2020). But even though the models perform important tasks, they also have to meet certain standards for complex structures that handle computational demands and offer significant benefits to various data attributes (De Biagi, 2014). All models have inherent limitations, such as potential biases in SVMs or difficulties processing long sequences in LSTMs. These highlight the continued need for future research to be improved even more.

In conclusion, this study utilizes machine learning models to show the path of technological breakthroughs poised to revolutionize machines’ acumen of human emotions. The development of these models is expected to result in systems that are highly developed and context-aware, thereby improving the interactivity and security of machine-mediated communications and applications over defferent field. This work underscores the changing nature of FER research and draft likely routes for critical future introductions essential for the growth of artificial intelligence in understanding human emotions.

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# Appendix:

**14TH FEBURARY 2024**

On 14th February 2024, we held our first meeting. During this meeting, each team member introduced themselves, paving the way for collaboration and exploration of our project.

We examined the machine learning assessment in order to identify the assigned task, task requirements, grading criteria, and overall purpose of the task. The main objective of this project was to write a literature review on any machine learning application of our choosing. In order to select the machine learning application to work on, each team member was allotted three votes to indicate their choices after which a brief discussion was held about the choices made. The Facial Emotion Recognition carried the highest vote hence it emerged as our chosen machine learning application topic to be reviewed by the team.

Arka Mandol suggested that each team member conducts research on different machine learning models that can be applied to the Facial Expression Recognition application. He also volunteered to work on the structure of the project. The team unanimously agreed that a WhatsApp group chat be created for ongoing communications and discussion. This was executed on February 15 by Nkemjika Ilokobi.

**21ST February 2024**

Our second meeting held on 21st of February 2024 with all team members in attendance. The primary focus of this meeting was the structure of the project that was proposed by team member Arka Mandol, the team deliberated and unanimously accepted his proposal.

Tasks were allocated to each member of the team with everyone in agreement to communicate our preferred machine learning model to be worked on via the WhatsApp platform created. During this meeting, a very crucial point of the project revolving around the citation methodology was raised. We agreed that the citation method to be used must be consistent throughout the document to uphold academic integrity. It was also emphasized that the use of AI generated content was explicitly prohibited during this project to mitigate the risk of academic misconduct. Team member Ifeoma Isiuwe volunteered to take the minutes of our meeting for record purposes.

To round up this meeting, we established deadlines for submission, the initial deadline was set for February 29, 2024, with a week grace period extending the final submission dates to March 6, 2024. We agreed that a Google Doc be created for this assessment task in order to facilitate collaboration. Team members were advised to maintain personal backup of their contribution

**29TH February 2024**

On the 29th of February 2024, a meeting was held with the primary objective of facilitating questions and providing clarification when needed. Arka Mandol conducted a thorough review of each team member's progress, identifying errors and addressing questions raised during the meeting. The structure of the project was further elaborated upon to ensure a comprehensive guide for each member in guiding their contributions. In this meeting, once again the importance of maintaining the integrity of our work was emphasized. To conclude this meeting a follow-up meeting was scheduled for 4 March 2024.

**4TH March 2024**

Our third meeting as a group was conducted on 4 March 2024, the main purpose of this meeting was to address inquiries and provide additional clarity as needed. Team member Ifeoma Isiuwe raised a concern about the aspects of handling the data set and modular structure, the team discussed briefly, and it was suggested that each team member review literature implementing our chosen machine learning models process on the data set. However, for further clarification, we unanimously agreed to speak with the lecturer for further guidance

Lilian Pang had inquired about the approach of conducting a comparative analysis. She was thereby advised to compare her model with the performance of other machine learning models used for facial expression recognition. In concluding this meeting, the team was reminded by Arka Mandol to ensure that our literature review is non-biased, and the content is from valid recent research papers, we also agreed on what count limits for each team member.

**6TH March 2024**

On 6 March 2024, we held our fifth meeting where the structure and template of the literature review project was reviewed with reference to the template provided on blackboard. Team member Arka Mandol presented separate templates and after a brief discussion, the team agreed on the best templates based on its compressive level of detailing. During this meeting specific sections of the project were assigned to team members to divide the workload evenly among us. Team member Lilian Pang was assigned to work on the introduction and conclusion sections of the literature review while Nkemjika Ilokobi and Ifeoma Isiuwe were assigned to work on the method and analysis section of the review. Finally, Arka Mandol and Sai Dheeraj were tasked to work on the discussion and evaluation section of the project. This allocation was based on the chosen templates to ensure consistency throughout the project. The team set a deadline for the submission of respective work on the selected models by March 7, this deadline was crucial, to ensure seamless compilation of the project, we also revisited references style to ensure uniformity across all sections. Further correspondence on the project was carried out via WhatsApp group chat due to the holiday.

**23RD APRIL 2024**

Our final meeting was held on 23 April 2024, during this meeting each team member reviewed the project to ensure that it was in line with the expectations provided on blackboard.

# Group Peer Assessment Form, Group [25]

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Name | ARKA | Linda | Lilian | Ifeoma | Sai Dheeraj |
| Student Number | W*23023023* | W22055838 | W23030767 | W23057234 | W23023865 |
| Signature |  |  |  |  |  |
| Date | 23/04/2024 | 23/04/2024 | 23/04/2024 | 23/04/2024 | 23/04/2024 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Criteria, Student | ARKA | Linda | Lilian | Ifeoma | Sai Dheeraj |
| Demonstration of relevant skills and knowledge | 6 | 5 | 5 | 5 | 6 |
| Attendance at group activities | 6 | 6 | 6 | 5 | 5 |
| Contribution to group activities | 5 | 5 | 5 | 6 | 6 |
| Contribution to agreed tasks outside of group meetings | 5 | 5 | 6 | 6 | 5 |
| Working for consensus on decisions and attempts to resolve conflict rather than promote it. | 5 | 6 |  | 5 | 5 |
| Trusts, supports, and respects other team members. | 6 | 5 | 5 | 5 | 6 |
| Ability to listen and interpret communication from other's points of view | 5 | 6 | 6 | 6 | 5 |
| Generates and promotes ideas and suggestions of their own | 5 | 5 | 5 | 6 | 5 |
| Considers and uses new ideas and suggestions from others | 6 | 6 | 6 | 5 | 6 |
| Average Score | 49/9=5.4 | 49/9= 5.4 | 49/9=5.4 | 49/9=5.4 | 49/9=5.4 |
| Individual contribution weighting | 49\*3/(24+30+31)= 1.72 | 49\*3/(24+30+31)= 1.72 | 49\*3/(24+30+31)= 1.72 | 49\*3/(24+30+31)= 1.72 | 49\*3/(24+30+31)= 1.72 |
| Rationale – What is the justification for the above? Each group member has contributed significantly to the success of this work. | | | | | |
| Every single member of the team participated and worked equally and efficiently to each project component. Their shows proper involvement, punctuality, and commitment to assigned tasks ensured a fair distribution of work and a successful project completion. They demonstrated outstanding collaboration and participation throughout the project by reaching decisions jointly, resolving conflicts fairly, and showing respect for one another. | | | | | |