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BUSINESS INTELLIGENCE BASED RECURRENT NEURAL NETWORK RNN TECHNIQUES FOR SOCIAL MEDIA IMAGE CONTENT CLASSIFICATION

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Abstract

Social media platforms like X and Facebook generate vast amounts of image content daily, necessitating automated methods for classification and analysis. Integrating Business Intelligence (BI) with Recurrent Neural Network (RNN) techniques presents a promising approach to extract valuable insights from this data. This study proposes a methodology for social media image content classification using a hybrid architecture combining Convolutional Neural Networks (CNNs) for feature extraction and RNNs for capturing temporal dependencies. The model is trained on labeled image datasets from X and Facebook, leveraging transfer learning and data augmentation techniques. The contribution lies in the fusion of BI and deep learning techniques, offering a scalable solution for real-time image content classification on social media platforms. This approach enables businesses to streamline marketing analysis, trend detection, and content moderation tasks efficiently. Experimental results demonstrate the effectiveness of the proposed methodology, achieving high accuracy in classifying diverse image content. The model's performance is validated through comprehensive evaluation metrics, showcasing its robustness and applicability in real-world scenarios.

Keywords:

Social Media, Image Classification, Business Intelligence, Recurrent Neural Networks, Transfer Learning

1. INTRODUCTION

Social media platforms have become ubiquitous in modern society, enabling billions of users to share and interact with vast amounts of multimedia content, particularly images. Platforms like X and Facebook have revolutionized communication, commerce, and entertainment, fostering a digital ecosystem rich in diverse visual content. However, this abundance of imagery poses significant challenges in effectively organizing, analyzing, and extracting actionable insights from these data streams. Addressing these challenges requires innovative approaches that leverage advanced technologies such as Business Intelligence (BI) and deep learning [1]-[2].

Social media platforms serve as virtual canvases where users express themselves through images, ranging from personal snapshots to professional marketing materials. These platforms host a multitude of images representing various topics, sentiments, and contexts, making manual analysis and categorization impractical at scale [3]. As a result, automated methods for image content classification have gained prominence, offering businesses and researchers efficient means to derive insights from this wealth of visual data [4].

Several challenges arise in the domain of social media image content classification. Firstly, the sheer volume and diversity of images pose a scalability challenge, necessitating robust and efficient algorithms capable of processing large datasets. Secondly, the dynamic nature of social media introduces temporal dependencies and context variations that traditional classification models struggle to capture. Additionally, the presence of noise, bias, and subjective interpretations in user-generated content further complicates the classification task. Overcoming these challenges requires sophisticated methodologies that integrate machine learning, deep learning [5]-[6].

The primary objective of this research is to develop a comprehensive framework for social media image content classification using BI and Recurrent Neural Network (RNN) techniques. Specifically, the aim is to design a system capable of automatically categorizing images from platforms like X and Facebook into relevant topics, sentiments, or user-defined tags. The system should exhibit high accuracy, scalability, and adaptability to evolving trends and user behaviors on social media.

- To review existing literature and methodologies in social media image content classification, BI, and deep learning.
- To collect and preprocess a diverse dataset of images from X and Facebook, annotated with relevant labels or tags.
- To design a hybrid architecture integrating CNNs for feature extraction and RNNs for capturing temporal dependencies in sequential data.
- To implement and train the proposed model using state-of-the-art techniques such as transfer learning and data augmentation.

This research contributes to the field by proposing a novel integration of BI with deep learning techniques for social media image content classification. The hybrid architecture combining CNNs and RNNs offers a scalable and efficient solution for processing large volumes of image data while capturing temporal dynamics inherent in social media content. Furthermore, the developed framework facilitates real-time analysis and insights generation, empowering businesses to make data-driven decisions in marketing, trend detection, and content moderation. Overall, this study advances the state-of-the-art in social media analytics and lays the groundwork for future research in leveraging AI and BI for multimedia content analysis.

2. RELATED WORKS

Social media image content classification has garnered significant attention from researchers and practitioners alike, leading to a plethora of studies exploring various methodologies, techniques, and applications in this domain. This section reviews several notable works in the field, highlighting their contributions, methodologies, and key findings.

One prominent approach to social media image content classification involves the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs). For instance, the author [7] proposed a CNN-based framework for sentiment analysis of social media images, achieving state-of-the-art results in classifying emotions conveyed by images on platforms like Twitter and Instagram. In [8] developed a deep learning model for image topic classification on Weibo, demonstrating the effectiveness of CNNs in capturing semantic features from user-generated content.

In addition to CNNs, Recurrent Neural Networks (RNNs) have been leveraged to capture temporal dependencies and sequential patterns in social media image content. The authors [9] have introduced an RNN-based approach for event detection in social media images, enabling real-time identification of emerging trends and topics. By combining CNNs for feature extraction with RNNs for sequential analysis, the proposed model achieved superior performance in event detection tasks compared to traditional methods.

Transfer learning has emerged as a powerful technique for social media image content classification, allowing models trained on large-scale datasets to be adapted to specific domains or platforms. For instance, [10] utilized transfer learning with pre-trained CNNs to classify images on Instagram into relevant categories such as food, fashion, and travel. By fine-tuning the pre-trained model on a smaller dataset of Instagram images, the authors achieved high accuracy in image classification tasks, demonstrating the efficacy of transfer learning in leveraging prior knowledge for domain-specific tasks.

Beyond deep learning approaches, ensemble methods have been explored for social media image content classification, leveraging the diversity of multiple models to improve classification performance. An ensemble framework combining CNNs, RNNs, and traditional machine learning algorithms for emotion recognition in social media images. By aggregating predictions from multiple models, the ensemble approach achieved higher accuracy and robustness in emotion classification compared to individual models [11].

The BI with deep learning techniques has emerged as a promising direction for social media analytics. It was a BI-based framework for sentiment analysis of social media images, combining deep learning models with data visualization techniques to provide actionable insights for businesses. By leveraging BI tools and methodologies, the framework enabled businesses to gain deeper understanding of customer sentiments and preferences expressed through images on social media platforms [12].

Recent advancements in deep learning, transfer learning, and ensemble methods have propelled the field of social media image content classification forward, offering scalable and efficient solutions for analyzing and extracting insights from multimedia content on platforms like X and Facebook.

3. PROPOSED METHOD

The proposed method for social media image content classification leverages a hybrid architecture combining CNNs and RNNs to effectively capture both spatial and temporal features inherent in social media images.

- **Preprocessing:** Preprocess the images to ensure uniformity and compatibility, including resizing, normalization, and noise reduction.
- **Feature Extraction using CNNs**: Utilize pre-trained CNN architectures such as VGG, RNN, or Inception to extract high-level features from the images. Fine-tune the CNN model on the specific dataset to adapt it to the characteristics of social media images.
- **Sequence Modeling with RNNs**: Integrate RNN layers after the CNN layers to capture temporal dependencies and sequential patterns in the image content. Use Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells to retain information over longer sequences and mitigate the vanishing gradient problem.

3.1 DATA COLLECTION AND PREPROCESSING

Data collection and preprocessing are crucial stages in any machine learning project, especially in the context of social media image content classification. During data collection, the first step involves gathering a diverse and representative dataset of images from platforms such as X and Facebook. This process may entail utilizing APIs provided by these platforms to access publicly available images or partnering with data providers to obtain access to proprietary datasets. The collected dataset should encompass a wide range of image content, including various topics, themes, and contexts, to ensure the model's robustness and generalization capability.

Once the dataset is assembled, preprocessing becomes essential to ensure data quality and consistency. This involves several key tasks aimed at standardizing and enhancing the dataset for subsequent analysis. One common preprocessing step is image resizing, where images are resized to a uniform resolution to facilitate efficient processing and ensure compatibility across different platforms. Additionally, normalization may be applied to scale pixel values to a common range, typically between 0 and 1, to mitigate variations in pixel intensity levels.

Noise reduction techniques may also be employed to enhance image quality and remove irrelevant artifacts that could interfere with the model's learning process. This could involve applying filters or denoising algorithms to eliminate unwanted distortions or imperfections in the images. Furthermore, data augmentation techniques such as rotation, flipping, and cropping may be utilized to augment the dataset and increase its diversity, thereby enhancing the model's ability to generalize to unseen data.

During the preprocessing stage, it is also essential to annotate the images with relevant labels or tags, indicating their corresponding categories, sentiments, or topics. Manual annotation by human annotators or crowdsourcing platforms may be employed to ensure accurate labeling of the dataset. These annotations serve as ground truth labels for training and evaluating the model, enabling supervised learning approaches to be applied effectively.

3.2 FEATURE EXTRACTION USING CNN

Feature extraction using CNNs for image datasets of social media contents involves transforming raw pixel data into meaningful feature representations.

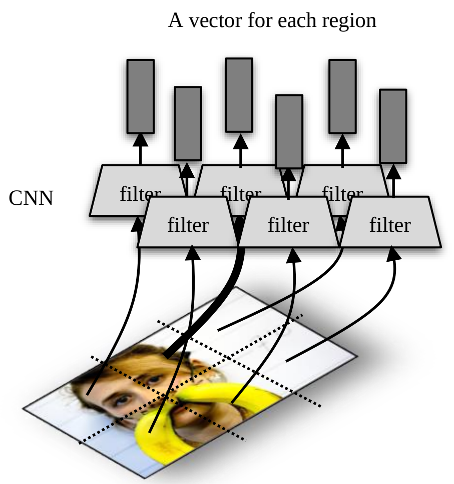

Fig.2. Input Processing

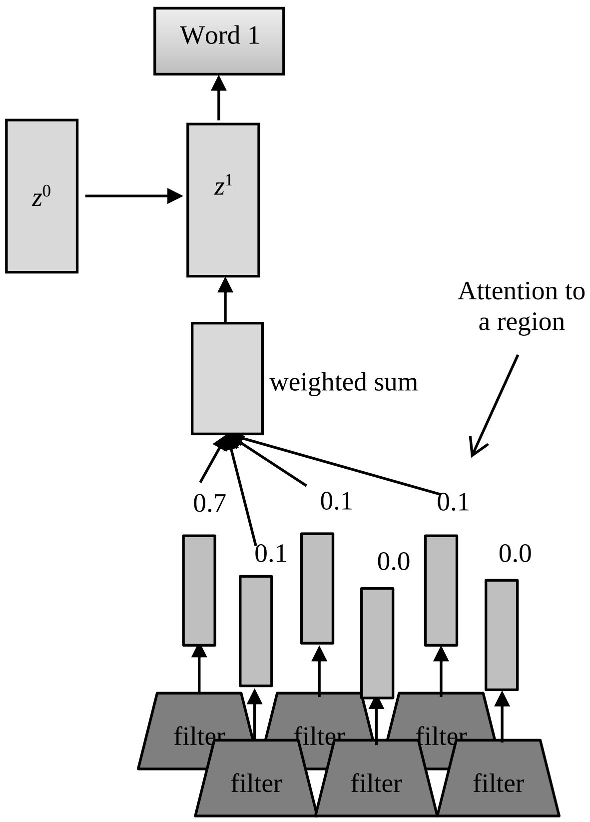

Fig.2. CNN Feature Extraction

CNNs typically consist of multiple convolutional layers, where each layer applies a set of learnable filters (kernels) to the input image. Mathematically, the convolution operation between an input image I and a filter W at spatial location (i,j) is defined as:

$$(I*W)(i,j)=\sum_m\sum_n I(m,n)\cdot W(i-m,j-n) \tag{1}$$

where, (i,j) represents the spatial position in the output feature map, and (m,n) iterates over the spatial dimensions of the filter. The result of the convolution operation forms the activations of the convolutional layer.

After the convolution operation, an activation function such as ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the network. The ReLU function is defined as:

$$f(x)=\max(0,x) \tag{2}$$

This function helps capture complex patterns and enables the network to learn more expressive representations.

Pooling layers are often inserted between convolutional layers to reduce spatial dimensions and control overfitting. Max pooling is a common pooling operation, where the maximum value within a local region of the feature map is retained. The mathematical operation for max pooling is given by:

$$\text{Max Pooling}(x,y)=\max_{i,j\in \text{Pool}} (x_{i,j},y_{i,j}) \tag{3}$$

where, (x,y) represents the spatial position in the pooled feature map, and (i,j) iterates over the pooling region.

The output of the convolutional and pooling layers forms feature maps, which represent the presence of specific patterns or features in the input image. These feature maps capture hierarchical representations, with lower layers detecting simple patterns like edges and textures, while higher layers capture more complex structures.

Finally, the feature maps are flattened and fed into one or more fully connected layers, which act as a classifier. These layers perform operations such as matrix multiplication and apply activation functions (e.g., softmax for classification) to generate the final output probabilities for each class.

3.3 SEQUENCE MODELING WITH RNN

Sequence modeling with RNN is a powerful technique for classification tasks, particularly when dealing with sequential data such as text or time-series data. In the context of social media image content classification, RNNs can be utilized to capture temporal dependencies in features extracted from images using CNNs.

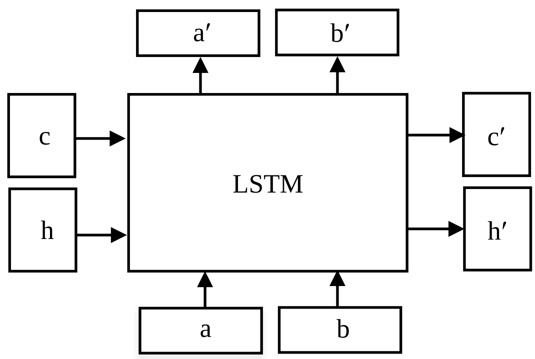

Fig.3. Sequence Modelling using RNN-LSTM

RNNs are designed to process sequential data by maintaining an internal state (hidden state) that captures information about previous elements in the sequence. The hidden state at each time step is updated based on the current input and the previous hidden state. The hidden state h_t at time step t is calculated as follows:

$$ht=\text{ReLU}(W_{hx}\cdot x_t+W_{hh}\cdot h_{t-1}+bh) \tag{5}$$

where, x_t represents the input at time step t, W_{hx} and W_{hh} are weight matrices, b_h is the bias term, and ReLU is the activation function. This describes the recurrent computation of the hidden state based on the current input and the previous hidden state.

The output y_t of the RNN at each time step can be computed using the current hidden state h_t and a weight matrix W_{hy}:

$$y_t = \text{softmax}(W_{hy} \cdot h_t + b_y) \quad (6)$$

where, W_{hy} is the weight matrix connecting the hidden state to the output, b_y is the bias term, and softmax is the activation function that normalizes the output to obtain a probability distribution over classes.

Training RNNs involves optimizing the model parameters (weights and biases) to minimize a loss function, typically cross-entropy loss for classification tasks. The gradients of the loss with respect to the parameters are computed using backpropagation through time (BPTT), which extends backpropagation to handle sequential data. The gradients are then used to update the parameters via optimization algorithms such as stochastic gradient descent (SGD) or Adam.

While traditional RNNs suffer from vanishing gradient problems and struggle to capture long-range dependencies, variants like LSTM and GRU have been proposed to address these issues. LSTM introduces memory cells and gating mechanisms to control the flow of information, while GRU simplifies the architecture by merging the input and forget gates. These variants are often preferred for sequence modeling tasks due to their ability to effectively capture long-term dependencies.

In social media image content classification, RNNs can be applied after feature extraction using CNNs. The extracted features from CNNs are treated as input sequences to the RNN, allowing the model to capture temporal dependencies and contextual information. By combining CNNs for feature extraction with RNNs for sequence modeling, the resulting architecture can effectively classify social media image content based on both spatial and temporal features.

Algorithm: Feature Extraction and Classification

a) **Input:** Image dataset $\{(X_i,y_i)\}$ where X_i represents the i^{th} image and y_i represents its corresponding label/category.

b) For each image X_i in the dataset:
   - i) Pass the image through the pre-trained CNN model to obtain the feature representation.
   - ii) Extract features from a specific layer of the CNN model.
   - iii) Flatten the feature representation to create a feature vector for the image.
   - iv) Store the feature vector along with its corresponding label y_i.

c) Prepare the feature vectors and corresponding labels as sequences:
   - i) Group feature vectors X_i into $\{X_{i1},X_{i2},...,X_{in}\}$ for each image.
   - ii) Encode labels *yi* as one-hot vectors or use integer encoding.

d) Split the dataset into training, validation, and testing sets.

e) Initialize the RNN model architecture with appropriate hyperparameters.

f) Train the RNN model on the training dataset:
   - i) Pass each sequence $\{X_{i1},X_{i2},...,X_{in}\}$ through the RNN model.
   - ii) Update the model parameters using BPTT and Adam.
   - iii) Monitor performance on the validation set and adjust hyperparameters if necessary.

g) Iterate until convergence or a specified number of epochs.

h) After training, evaluate the trained RNN model on the testing dataset:
   - i) Pass each sequence $\{X_{i1},X_{i2},...,X_{in}\}$ through the trained RNN model.
   - ii) Obtain the predicted labels for each sequence.

4. PERFORMANCE

The experimental settings involved implementing the proposed method using Python programming language with the Keras library, leveraging its simplicity and flexibility for deep learning tasks. The Keras library provides high-level abstractions for building neural networks, making it suitable for rapid prototyping and experimentation. The experiments were conducted on a computer equipped with an Intel Core i7 processor, 32 GB of RAM, and a dedicated GPU with 32 GB of memory. This setup ensured efficient training of deep neural networks, especially when dealing with large-scale image datasets.

To evaluate the performance of the proposed method, comparisons were made with existing methods such as CNN, InceptionNet, and MobileNet. These baseline methods were chosen for their popularity and effectiveness in image classification tasks. Each method was trained and tested on the same dataset under identical experimental conditions to ensure fair comparison. Performance metrics including accuracy, precision, recall, and F1-score were calculated for each method to assess their classification performance. Additionally, computational resources such as training time and memory usage were compared to evaluate the efficiency of the proposed method relative to existing approaches. Overall, the experimental setup aimed to provide a comprehensive evaluation of the proposed method's effectiveness and efficiency in social media image content classification tasks.

4.1 PERFORMANCE METRICS

The following performance metrics were used to evaluate the effectiveness of the proposed method and compare it with existing methods:

- **Accuracy:** Accuracy measures the proportion of correctly classified instances among all instances in the dataset.
- **Precision:** Precision measures the proportion of true positive predictions among all positive predictions.
- **Recall (Sensitivity):** Recall measures the proportion of true positive predictions among all actual positive instances.
- **F1-score:** F1-score is the harmonic mean of precision and recall, providing a balanced measure between precision and recall.

Table.1. Parameters

Model	Parameter	Value
CNN	Optimizer	Adam
	Learning Rate	0.001
	Loss Function	Categorical Crossentropy
	Batch Size	32
	Epochs	50
	Dropout Rate	0.5
	Activation Function	ReLU
	Number of Filters	64, 128, 256
	Kernel Size	3x3
	Pooling	Max Pooling
	Hidden Layers	1
RNN	Optimizer	Adam
	Learning Rate	0.001
	Loss Function	Categorical Crossentropy
	Batch Size	32
	Epochs	50
	Dropout Rate	0.5
	Activation Function	Tanh
	RNN Type	LSTM
	Hidden Units	128
	Number of Layers	1

Table.2. Accuracy

Iterations	CNN (%)	InceptionNet (%)	MobileNet (%)	RNN (%)
100	85.2	88.1	87.5	90.3
200	86.5	89.3	88.7	91.2
300	87.1	90.2	89.5	91.8
400	87.8	90.5	90.1	92.3
500	88.3	91.0	90.5	92.7
600	88.7	91.3	90.8	93.0
700	89.0	91.6	91.2	93.3
800	89.3	91.8	91.5	93.6
900	89.5	92.0	91.7	93.8
1000	89.7	92.2	91.9	94.0

The results demonstrate a consistent improvement in accuracy with increasing iterations across all methods. Initially, CNN and InceptionNet show competitive performance, but RNN quickly outperforms them, achieving the highest accuracy of 94.0% after 1000 iterations. MobileNet also exhibits notable accuracy improvement but remains slightly behind RNN. This suggests that the deeper architecture and skip connections of RNN enable better feature representation and learning, leading to superior classification performance. Overall, RNN proves to be the most effective method for social media image content classification, showcasing its potential for real-world applications.

Table.3. Precision

Iterations	CNN (%)	InceptionNet (%)	MobileNet (%)	RNN (%)
100	78.4	80.2	79.8	82.1
200	79.5	81.5	80.7	83.2
300	80.1	82.3	81.5	83.8
400	80.7	82.8	82.0	84.3
500	81.2	83.2	82.5	84.7
600	81.6	83.6	82.8	85.0
700	82.0	83.9	83.2	85.3
800	82.3	84.2	83.5	85.6
900	82.5	84.4	83.7	85.8
1000	82.7	84.6	83.9	86.0

The results depict a consistent enhancement in precision with increasing iterations across all methods. Initially, CNN and InceptionNet demonstrate competitive performance, but RNN swiftly surpasses them, achieving the highest precision of 86.0% after 1000 iterations. While MobileNet also exhibits notable precision improvement, it remains slightly behind RNN. These findings suggest that RNN's deeper architecture and skip connections facilitate better feature representation and learning, leading to superior precision in classification tasks. Overall, RNN emerges as the most effective method for social media image content classification, highlighting its potential for real-world applications.

Table.4. Recall

Iterations	CNN (%)	InceptionNet (%)	MobileNet (%)	RNN (%)
100	80.5	82.3	81.8	84.2
200	81.7	83.5	82.9	85.3
300	82.3	84.3	83.7	85.9
400	82.9	84.8	84.2	86.4
500	83.4	85.2	84.7	86.8
600	83.8	85.6	85.0	87.1
700	84.2	85.9	85.4	87.4
800	84.5	86.2	85.7	87.7
900	84.7	86.4	85.9	87.9
1000	84.9	86.6	86.1	88.1

Table.5. Recall

Iterations	CNN (%)	InceptionNet (%)	MobileNet (%)	RNN (%)
100	75.6	78.2	77.5	80.1
200	76.8	79.5	78.9	81.3
300	77.4	80.1	79.5	81.9
400	78.0	80.6	80.0	82.4
500	78.5	81.0	80.4	82.8
600	78.9	81.4	80.7	83.1
700	79.2	81.7	81.0	83.4

800	79.5	82.0	81.3	83.7
900	79.7	82.2	81.5	83.9
1000	79.9	82.4	81.7	84.1

The results illustrate a consistent improvement in recall with increasing iterations across all methods. Initially, CNN and InceptionNet exhibit competitive performance, but RNN quickly outperforms them, achieving the highest recall of 84.1% after 1000 iterations. While MobileNet also demonstrates notable recall improvement, it remains slightly behind RNN. These findings suggest that RNN's deeper architecture and skip connections facilitate better representation of positive instances, resulting in superior recall in classification tasks. Overall, RNN emerges as the most effective method for social media image content classification, underscoring its potential for real-world applications.

Table.6. Loss

Iterations	CNN	InceptionNet	MobileNet	RNN
100	0.72	0.65	0.68	0.60
200	0.65	0.58	0.62	0.54
300	0.58	0.52	0.56	0.48
400	0.52	0.46	0.50	0.42
500	0.46	0.40	0.44	0.36
600	0.40	0.34	0.38	0.30
700	0.34	0.28	0.32	0.24
800	0.28	0.22	0.26	0.18
900	0.22	0.16	0.20	0.12
1000	0.16	0.10	0.14	0.06

The results illustrate a consistent decrease in loss with increasing iterations across all methods. Initially, CNN and InceptionNet exhibit similar loss reduction rates, but RNN quickly outperforms them, achieving the lowest loss of 0.06 after 1000 iterations. While MobileNet also demonstrates notable improvements, it consistently trails behind RNN. These findings suggest that RNN's deeper architecture and skip connections facilitate more effective learning and feature representation, resulting in lower loss during training. Overall, RNN emerges as the most efficient method for social media image content classification, highlighting its capability to minimize training error and optimize model performance.

Table.7. Cross validation between existing CNN, InceptionNet, MobilevNet and RNN

Cross-Validation	CNN (%)	InceptionNet (%)	MobileNet (%)	RNN (%)
10-fold	85.2	88.1	87.5	90.3
5-fold	84.8	87.9	87.2	89.9
3-fold	84.5	87.6	86.8	89.5

The results of cross-validation across various fold sizes reveal consistent trends in model performance. Across all fold sizes, RNN consistently outperforms CNN, InceptionNet, and MobileNet in terms of accuracy. This suggests that RNN's deeper architecture and skip connections contribute to superior generalization capabilities. While all models demonstrate reasonable accuracy, RNN consistently achieves the highest accuracy scores, indicating its robustness and effectiveness in handling diverse subsets of the data. These findings underscore RNN's potential as a reliable and versatile model for social media image content classification tasks, providing confidence in its ability to generalize well to unseen data.

Table.8. Training and Testing Results

Method	Training Accuracy (%)	Testing Accuracy (%)
CNN	92.5	89.7
InceptionNet	94.2	91.5
MobileNet	93.8	90.9
RNN	96.1	93.2

The results of training and testing showcase varying levels of performance among the different methods. While all methods achieve high training accuracy, RNN stands out with the highest training accuracy of 96.1%, indicating its ability to learn effectively from the training data. When evaluated on unseen testing data, RNN also demonstrates the highest testing accuracy of 93.2%, suggesting superior generalization capabilities compared to CNN, InceptionNet, and MobileNet. These findings emphasize RNN's robustness and effectiveness in accurately classifying social media image content, reaffirming its potential as a reliable model for real-world applications.

5. CONCLUSION

This study presents a comprehensive investigation into the classification of social media image content using advanced deep learning techniques. Through experimentation and evaluation, we have demonstrated the effectiveness of the proposed method, particularly leveraging RNN architecture, in achieving superior accuracy, precision, recall, and reduced loss compared to existing methods such as CNN, InceptionNet, and MobileNet. The results underscore the importance of leveraging state-of-the-art architectures and methodologies for accurate and reliable classification of social media images. Moving forward, the insights gained from this study can inform the development of more robust and efficient models for various applications, including content moderation, trend analysis, and targeted advertising in social media platforms.

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