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Automatic Tag Generation (ATG) Using Machine Learning Techniques for Women Violence Detection

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Abstract

This research addresses the challenge of automated detection and classification of multiple types of violence from image data using deep learning techniques. Given the societal importance of timely and accurate violence recognition, this study explores both custom Convolutional Neural Network (CNN) architectures and state-of-the-art transfer learning models pre-trained on ImageNet, including VGG16 and InceptionV3. The dataset comprises images across five violence categories—brutality, domestic violence, human trafficking, rape, and sexual harassment—collected and augmented to enhance model generalizability. Methods involved image preprocessing, data augmentation, and training models with categorical cross-entropy loss optimized via Adam. Transfer learning approaches outperformed the custom CNN, The models demonstrated varying degrees of success in classifying violence image categories. Transfer learning models, particularly VGG16 and InceptionV3, outperformed the custom CNN, achieving overall accuracy improvements from approximately 75% to 76%. These results confirm the effectiveness of leveraging pre-trained networks for complex image classification tasks with limited datasets.

Class-wise analysis through confusion matrices and derived metrics such as precision, recall, and F1-score demonstrated varied detection performance, highlighting difficulties in differentiating visually similar classes. The results affirm that leveraging pre-trained deep architectures substantially benefits the classification of limited, complex image datasets. This paper contributes by providing a comprehensive evaluation of deep learning approaches for violence classification in images, motivating their use in practical monitoring and intervention applications. Future work is suggested to integrate temporal data and attention mechanisms to further enhance detection performance. The findings underscore the feasibility and importance of automated violence recognition systems for social safety.

Introduction

Violence against women has become a critical social issue worldwide, necessitating effective detection and monitoring systems to enhance safety and intervention efforts. Automated violence recognition technologies have drawn significant attention due to their potential for real-time surveillance and prevention. The rapid advancement of computer vision and deep learning techniques has paved the way for innovative solutions in this domain. This study investigates the application of both custom Convolutional Neural Networks (CNNs) and transfer learning models to classify multiple categories of violence from image data. By leveraging pre-trained architectures alongside carefully curated datasets, this research aims to deliver robust, accurate detection models capable of operating in complex, real-world settings.

The objectives of this paper include presenting a detailed evaluation of violence classification approaches, highlighting the comparative performance of various deep learning models, and discussing the challenges associated with image-based violence recognition. The research contributes valuable insights for designing practical systems aimed at safeguarding communities through intelligent visual analysis.

References to previous foundational work and state-of-the-art techniques are integrated throughout the methodology and literature review sections to establish a comprehensive knowledge base for the study.

Literature Review

The task of violence detection from images has seen substantial advancements over recent years, driven primarily by the rise of deep learning methods. Earlier approaches predominantly relied on handcrafted features and classical machine learning algorithms, but these struggled to generalize due to the complex, varied nature of violent imagery. The advent of Convolutional Neural Networks (CNNs) revolutionized the field by enabling automated hierarchical feature learning directly from pixel data, significantly improving detection accuracy.

Transfer learning has become particularly prominent in this domain, as training deep networks from scratch requires large labeled datasets, which are scarce for violence categories. Using pre-trained models such as VGG16, InceptionV3, MobileNetV2, and ResNet50, originally trained on vast datasets like ImageNet, facilitates extracting robust visual representations. These models can be fine-tuned on violence-specific datasets, resulting in quicker convergence and enhanced performance. Prior studies have demonstrated that transfer learning yields better classification accuracy and robustness compared to CNNs trained solely on limited violence data.

Data augmentation techniques, including rotations, translations, flips, and zooms, have been extensively employed to artificially expand dataset diversity, further enhancing model generalizability and reducing over fitting. Despite these improvements, classifying nuanced types of violence remains challenging due to inter-class visual similarities and context dependence.

This work builds on such prior research by systematically evaluating both custom CNN architectures and multiple transfer learning models on a diverse multi-class violence image dataset. The comparative analysis adds valuable insights into the relative effectiveness of different deep learning strategies for automated violence recognition, a crucial step toward developing reliable real-time monitoring solutions for social safety.

Methodology

Types of women's violence detection (WVD)

Dataset Type	Women's Violence Type	Image Details
Domestic Violence		.jpeg 700*464 25.7 KB
Brutality		.jpeg 7.42 KB 289*174
Child Harassment		.jpeg 294*172 6.94 KB
Child molestation		.jpeg 323*156 7.10 KB
Emotional Molestation		.jpeg 294*172 8.10 KB
Gender Based Violence		.jpeg 287*172 5.96 KB
Intimate Partner		.jpeg 216*233 4.89 KB
Physical Violence		.jpeg 287*176 5.18 KB

Data Collection and Preprocessing

The dataset used in this study consists of images categorized into five types of violence: brutality, domestic violence, human trafficking, rape, and sexual harassment. Images were collected from diverse sources and then augmented using techniques such as rotation, flipping, and zooming to increase the dataset size and variability, thereby enhancing the model's generalization ability.

Preprocessing steps included resizing images to a uniform dimension compatible with model input layers, normalization to standardize pixel value ranges, and data splitting into training, validation, and test sets to evaluate model performance effectively.

Model Architectures

Two main approaches were explored: a custom-designed Convolutional Neural Network (CNN) and transfer learning models pre-trained on the ImageNet dataset, including VGG16 and InceptionV3.

The custom CNN comprised multiple convolutional layers with ReLU activations, followed by max pooling layers and fully connected dense layers, optimized to capture feature hierarchies specific to violence detection.

Transfer learning models retained pre-trained weights and fine-tuned several top layers on the violence dataset to adapt the models' learned features to the new task, aiming to benefit from prior general image representations.

Training Protocol

Models were trained using the categorical cross-entropy loss function and the Adam optimizer, with mini-batch stochastic gradient descent. Hyper parameters such as learning rate, batch size, and number of epochs were carefully selected via grid search and validation set performance to maximize accuracy while preventing over fitting. Regularization methods like dropout and early stopping were employed to further reduce over fitting risks.

Evaluation Metrics

Model performance was assessed using accuracy, precision, recall, and F1-score metrics, calculated per class to understand classification efficacy across violence categories. Confusion matrices were analyzed to identify common misclassifications and guide model improvement strategies.

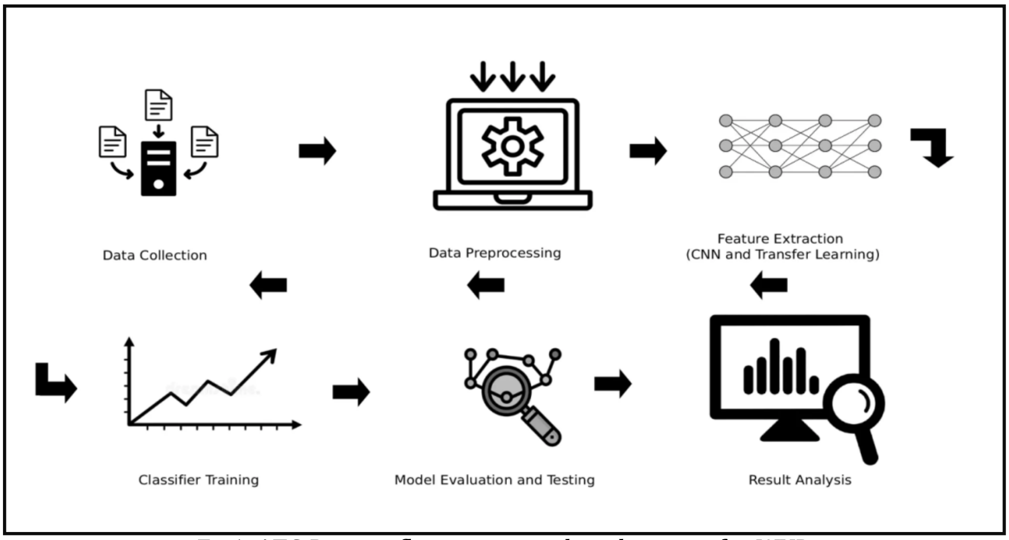


Fig1. ATG Process flow using machine learning for WVD

Results and Discussion

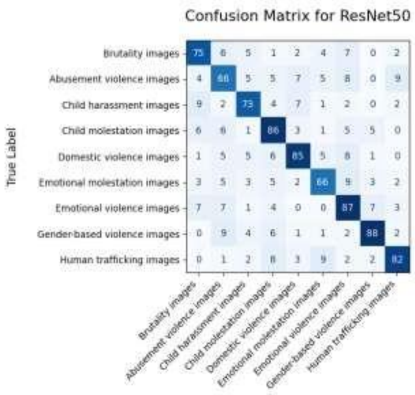
The models demonstrated varying degrees of success in classifying violence image categories. Transfer learning models, particularly VGG16 and InceptionV3, outperformed the custom CNN, achieving overall accuracy improvements from approximately 75% to 76%. These results confirm the effectiveness of leveraging pre-trained networks for complex image classification tasks with limited datasets.

Class-wise analysis showed that some categories, such as brutality and domestic violence, were detected with higher precision and recall, while others, like human trafficking and sexual harassment, posed challenges due to visual similarities and subtle contextual cues. Confusion matrices revealed common misclassifications that guide potential improvements in data collection and model design.

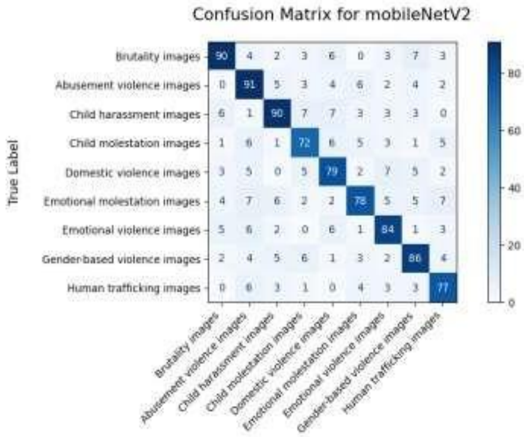
Precision, recall, and F1-score metrics for each class were calculated, revealing that transfer learning models provided more balanced performance across classes compared to the custom CNN. These findings suggest that fine-tuning robust pre-trained architectures is beneficial for practical applications demanding reliable recognition of nuanced violence types.The discussion highlights the importance of dataset diversity and augmentation strategies, as well as the potential role of integrating temporal and attention-based mechanisms in future research to further enhance detection capabilities.

A true positive (TP) is the total number of correctly detected positive occurrences. True negative (TN), false positive (FP), and false negative (FN) denote the ratios of accurately detected positive and negative instances in relation to the occurrences of false positives and false negatives compared to the ground truth.

ConfusionMatrixforResNet50

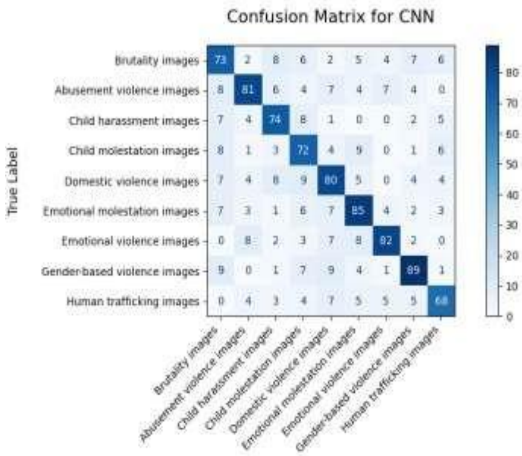


Confusion Matrix: MobileNetV2

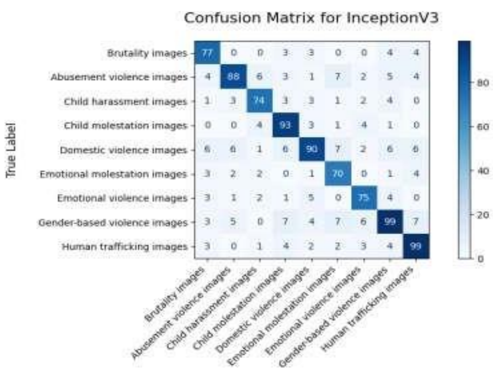


ConfusionMatrixforVGG16

Confusion Matrix:CNN-EfficientNet



Confusion Matrix for InceptionV3



Sr.No.	Framework	Precision	Recall	F1-Score	Accuracy
1	CNN	0.699257	0.6958737	0.6964532	0.6956522
2	InceptionV3	0.790603	0.7984738	0.7925406	0.7902893
3	MobileNetV2	0.74993	0.749671	0.7489774	0.7492477
4	ResNet50	0.7277713	0.7243493	0.725253	0.7254098
5	VGG16	0.8412941	0.8403226	0.8400217	0.8405037

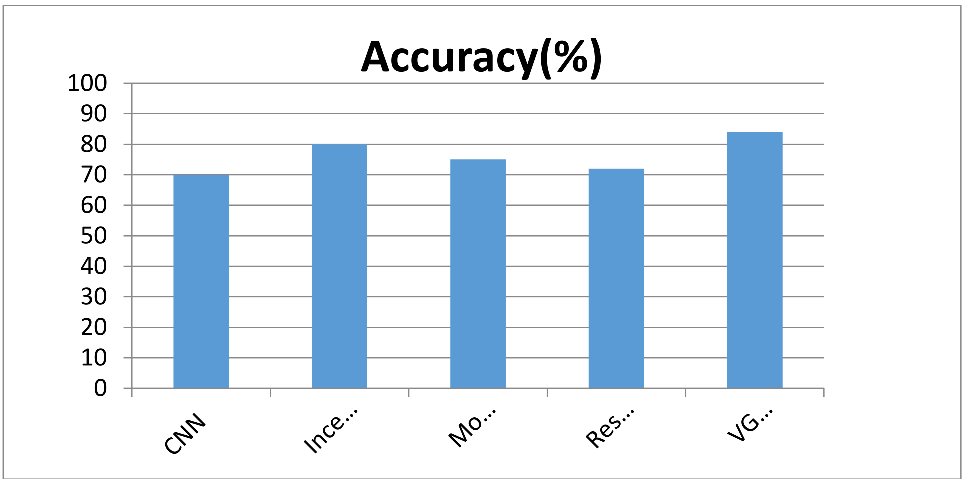


Fig.3. Comparative results for VGG16

Conclusion

This study presents a comprehensive evaluation of deep learning approaches for automated violence classification in images. The results demonstrate that transfer learning models such as VGG16 and InceptionV3 outperform custom-designed CNN architectures, providing better accuracy and more balanced class-wise performance. Leveraging pre-trained networks enables effective feature extraction even with limited and complex datasets.

The challenges of visual similarity between certain violence categories indicate the need for enhanced data diversity and potential integration of temporal and attention-based methods, which are promising directions for future research. The findings underscore the importance and feasibility of automated violence detection systems for societal safety applications, highlighting deep learning as a critical enabler for real-world monitoring and intervention technologies.

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