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Ethical Analysis of Online Media Journalistic Photos Worth Publishing Based on Images Using the Convolutional Neural Network Method

Syamsul Rijal [1], Aslam Mardin [2], Anas [3], Tirta Chiantalia Sharif [4], Sunardi [5]
Computer Systems, Handayani University Makassar [1,2,3,4]
Informatics Engineering, Undipa University Makassar [5]
syamsulr8@gmail.com [1], aslam11mardin@gmail.com [2], anas.daeng.pasewang@gmail.com [3], tirtashariff@gmail.com [4], sunardi@undipa.ac.id [5]

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ABSTRACT

This study aims to develop and test a Convolutional Neural Network (CNN)-based artificial intelligence model to analyze and classify online media journalistic photos based on ethical criteria for publication suitability (suitable or unsuitable). In the context of digital journalism, the process of filtering sensitive visual content that potentially violates the code of ethics is often time-consuming and prone to subjectivity. Therefore, a CNN model is proposed as an automated solution to identify images containing visual elements deemed unethical. An annotated image dataset was used to train and test the CNN model. The model test results showed effective and robust performance in classifying the ethical suitability of photos. The model achieved a weighted average accuracy of 0.86 (86%) and a weighted average F1 - score of 0.86. Specifically, the model performed very well in identifying "suitable" photos with precision, recall, and F1- score values ranging from 0.88 to 0.89. Performance in the "Unsuitable" class was also relatively strong with an F1 - score of 0.81. Overall, these results confirm that the CNN method has great potential as an efficient and objective decision support system in the visual content editing process. Implementing this model not only speeds up the editorial process but also improves online media's adherence to journalistic ethical standards by minimizing the risk of publishing potentially unethical photos.

I. INTRODUCTION

The world of online journalism is fraught with challenges closely related to applicable laws governing the reporting process, particularly for photos circulating in various Indonesian online media outlets. The practice of publishing photos in various media outlets shows that some still do not meet journalistic ethical standards. Therefore, this study seeks to offer a technology-based solution to assist editors in selecting photos suitable for publication in accordance with journalistic codes of ethics.

In the world of journalism, photojournalism ethics plays a crucial role in maintaining media credibility. According to journalistic ethics theory, published photos must adhere to the principles of accuracy, honesty, and avoid misleading the audience. In her journal (Ismayati, 2022), she cited data from the National Press Photographers Association (NPPA), which stipulates ethical standards that journalistic photos must depict reality objectively without manipulation that could mislead. This demonstrates the need for a system to help assess the ethical suitability of photos before publication.

Furthermore, the development of artificial intelligence technology, particularly in the field of image processing, has enabled the automation of various tasks that previously could only be done manually. In his journal (WSE Putra, 2016), Convolutional Neural Network (CNN) is defined as a method in deep learning that has proven effective in image classification and analysis. (Nugroho et al., 2020) CNN can be used to detect elements in photos and assess their compliance with journalistic ethical standards. Thus, this approach offers efficiency for the media in selecting photos before publication.

Several previous studies have shown that CNNs can be applied in image analysis for various purposes, including medical, security, and facial recognition (Pariyasto et al., 2025). In the journalistic context, the use of CNNs to assess the suitability of journalistic photos is still rare. Therefore, this research is expected to contribute to technological developments in journalism by presenting an automated system that can assist editors in the photo selection process.

Based on data collected from various online media, photographs are still found that violate the journalistic code of ethics, such as image manipulation, the use of photos that are not in accordance with the context of the news, and depictions that are disrespectful to the subjects in the photos. This shows that there is still a need for an automated system that can help identify these violations efficiently. Based on this background, the main contribution (novelty) of this study is the integration of artificial intelligence based on Convolutional Neural Networks that are explicitly based on the principles of the Indonesian Journalistic Code of Ethics, offering an objective decision support solution that has not been widely studied in the context of national digital media.

II. Method

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A. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of artificial neural network specifically designed to process image or visual data. CNNs are inspired by the way the human visual cortex works to recognize patterns and objects. CNNs are widely used in image classification, object detection, facial recognition, and photojournalism analysis to detect ethical violations. Compared to conventional artificial neural networks (Multilayer Perceptrons), CNNs are superior in image analysis because they can automatically extract important features from images through convolution and pooling processes. Convolutional Layer This layer extracts features by applying a filter (kernel) to the input image. The convolution operation can be expressed as:

$$Y(i,j) = \sum_{m} \sum_{n} X(i-m, j-n) \cdot K(m,n)$$

$X(i)$is the input image,
$(m,n)$is the kernel (filter),
$Y(i,j)$is the convolution result. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

The Convolutional Neural Network (CNN) architecture used in this study is a pretrained model that has been previously trained on a large-scale dataset, such as ImageNet or other relevant datasets. The use of pretrained models was chosen because of their efficiency in the training process, as well as their ability to recognize common visual features such as shapes, objects, and facial expressions, which are very important in the context of classifying journalistic photos as suitable for publication or not. In its implementation, adjustments were made to the final layer (fine-tuning) so that the model could adapt to the specific characteristics of the journalistic photo dataset used in this study. This approach is considered effective because it can save computational resources and training time, without sacrificing classification performance. The CNN model used to identify unethical elements in journalistic photos in this study is ResNet50 with a multi-modal fine-tuning technique with parameters of Epoch: 20, Batch Size: 64, Learning Rate: 64. The training data was divided with a percentage of 80:20 train : test (validation split test). The following is an example Photo ethics based on the Press Council's Code of Journalistic Ethics (KEJ).

TABLE I
KEJ PRESS COUNCIL PHOTO

No	Can Be Detection CNN	Press Council KEJ Reference	Information
1	Pornograph y	Strictly prohibited (Article 4 of the Code of Criminal Procedure). Definition: Depictions of erotic behavior that solely arouse lust.	Islamic media tends to have stricter filters on images that show minimal clothing, body contours, or nudity, even if the intent is not purely sexual (e.g., human interest photos on the beach).
2	Blood	Strictly prohibited (Article 4 of the Code of Criminal Procedure). Definition: Cruel and merciless behavior. Focus on avoiding visualizations of sadism.	Islamic media tends to be more careful in showing explicit images of dead or seriously injured victims (blood), focusing on humanitarian/preachin g messages rather than shock value.
3	Minor children)	Protected (Article 5 of the KEJ). The identities of victims of sexual crimes and child perpetrators must not be	There is a high level of concern that photographs of children, especially girls, do not violate norms of decency or invite slander, even if only in the context of ordinary news.

		mentioned or broadcast. Traumatic experiences must be respected.	
4	Expression of Suffering	Respect for privacy (Article 2 of the Code of Criminal Procedure) and the presumption of innocence (Article 3 of the Code of Criminal Procedure) are mandatory. The faces of perpetrators/victims are often obscured.	The emphasis on disguising faces (especially of suspects or innocent victims) has become stronger in Islamic media as a form of moral responsibility and preserving individual honor.

B. Data types and sources

The data used in this study consists of digital images of journalistic photos obtained from various online media sources. Data collection was conducted by combining data from several online news portals operating in the Makassar region, such as radarmakassar.com, inikata.co.id, and fajar.co.id. Additionally, some data was also taken from other relevant online sources to enrich the content variety and visual context within the dataset.

The data covers a wide range of event categories, from general news and crime to disasters and social activities, and is expected to represent real-world conditions frequently encountered in visual reporting on online media. The entire dataset will use .jpg and .png file formats.

TABLE 2
TOTAL IMAGE DATASET

No	Category	Total Data	Train	Test	Data source
1	Pornography	6149	4919	1230	Hungingface
2	Blood	484	392	92	Google image
3	Age	24106	19284	4822	Hungingface
4	Expression	35887	28709	7178	Kagle

C. System design and test scenarios

This journalistic ethics violation detection system was designed to evaluate the ability of a Convolutional Neural Network (CNN) model to identify images that violate journalistic codes of ethics. The dataset used will be divided into two classes, "appropriate" and "unappropriate," based on the Indonesian Press Council's guidelines regarding visualization in news reporting. CNN-based systems have the potential to contain dataset bias; therefore, this study links the classification results to the journalistic code of ethics (KEJ) developed in collaboration with the validator. The validator who was invited to collaborate in this research was Muhammad Yunus. Certification Type: Main Journalist. Press Council Certification: 2327-AJI/WU/DP/VII/2017/20/5/84 .

The following rules will be used as a classification of journalistic ethics theories and principles.

TABLE 3
CLASSIFICATION FORMULATION RULES

News Topics	Minors	Expression of Suffering	Blood Detection/ Wound	Pornography/Indecency Detection
Criminal	Not fit for publication	Not fit for publication	Not fit for publication	Not fit for publication
Health	worthy of publication	Not fit for publication	Not fit for publication	Suitable for publication (only if in an educational/medical context)
Tragedy	Not suitable for publication	Not suitable for publication	Not suitable for publication	Not suitable for publication
Entertainment	worthy of publication	Suitable for publication	Suitable for publication	Not suitable for publication
Sport	Suitable for publication (only if reasonable, e.g. competition)	Suitable for publication	Not suitable for publication (if the injury is very serious)	Suitable for publication

Testing was conducted by dividing the dataset into eligible and ineligible data to create classes that differentiate elements. To ensure model generalization, testing was conducted using test data that the model had never seen during training. Furthermore, the use of a validator also strengthened the validity of this study. Several test scenarios were developed, such as Testing of images containing blood stains, pornography of suffering expressions and minors.

III. RESULTS AND DISCUSSION

The ability of the Convolutional Neural Network (CNN) method to analyze the ethical feasibility of journalistic photos in image-based online media. This research focuses on identifying visual elements deemed sensitive or violating publication ethics. The results presented include the model testing process, image object detection performance using CNN, and validation of the results against applicable journalistic ethics standards. This presentation aims to provide an objective overview of the system's ability to automatically detect visual ethics violations.

A. Description of the Results of the System Built

The system developed in this study is designed to automatically analyze the ethical feasibility of journalistic photos in online media using an image-based approach through the Convolutional Neural Network (CNN) method. This system was developed to assist editorial decision-making regarding the ethical feasibility of publishing a photo in the form of images of suffering, expressions, and faces of minors. The system architecture consists of several main components, namely an image preprocessing module, a CNN model for object or expression classification, and a visual interface for displaying detection results. The CNN model used is the result of fine-tuning of a pretrained model to suit the needs of the journalistic context, and is integrated into a Google Colab / Jupyter-based testing platform to facilitate the experimentation and validation process. This system was developed to assist editorial decision-making regarding the ethical feasibility of publishing a photo in online media platforms.

B. System Implementation Results

The following displays the results of the successfully created CNN model application, which includes several detection features. The system processes images to identify specific visual features that are key indicators in assessing the suitability of journalistic photos. This process is the core of the image-based approach, enabling the model to understand the visual content of online media. The Convolutional Neural Network (CNN) model detects four main objects: blood, expressions of distress, age, and pornography. The following is a detailed image of each detection feature:

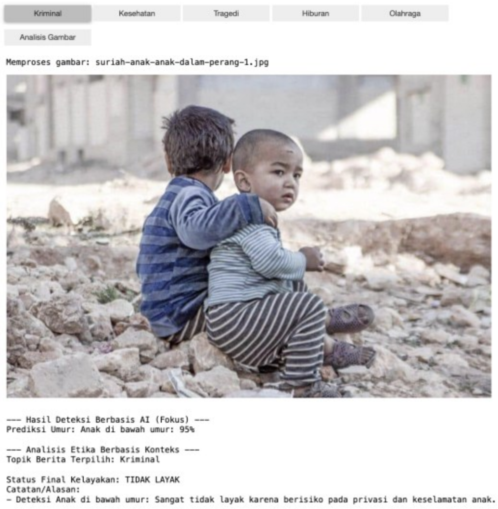


Figure 1. Results of the underage child detection model

This detection specifically identifies the presence of minors in a photo. Given that child protection is a very strict ethical principle in journalism, photos featuring children are carefully reviewed. The model is trained to distinguish the facial features of children from those of adults. Even with detection, the appropriateness of photos of children depends heavily on the context. Photos of children participating in sports or educational events are considered appropriate if they do not violate their privacy or pose a risk. However, photos of children in the context of crime, tragedy, or exploitation are immediately classified as inappropriate . With this age-detection image, after the user uploads an image (via an intuitive drag-and-drop feature for .jpg or .png files) and presses the "Process" button, the system quickly analyzes the image. The results show "Image contains minors 95% detection," indicating that the system has the ability to identify potentially sensitive or unpublishable content.

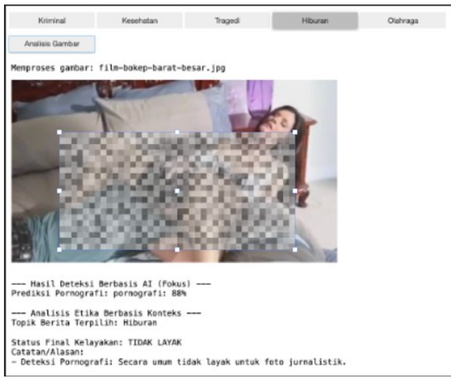


Figure 2. Results of the child pornography detection model

The pornography detection feature aims to identify content that is explicitly inappropriate and violates public ethics and regulations. The model is trained to recognize patterns associated with pornography, sexual acts, and other obscene content. In the context of photojournalism, this detection is absolute. If the model detects pornographic content, the photo will automatically be classified as inappropriate regardless of the news context, as such content is universally considered inappropriate for public consumption. In this pornography detection feature, after the user uploads an image (via an intuitive drag-and-drop feature for .jpg or .png files) and presses the "Process" button, the system quickly analyzes the image. The result shows "Image contains 88% nudity," indicating that the system has the ability to identify potentially sensitive pornographic content.

The blood detection feature aims to identify the presence of visual elements that indicate violence, accidents, or injuries. The model is trained to recognize color patterns, textures, and shapes associated with blood in various conditions, whether on clothing, surfaces, or the body. While this detection is crucial for sensitive issues, the final decision on appropriateness will still consider the context of the accompanying news. For example, a photo of blood in the context of a crime news story will be considered inappropriate, while in the context of health news (e.g., surgical procedures or blood donations) it will be considered appropriate. The following displays the results of the CNN Model application that has been successfully created with a feature that will process image data that can be uploaded and can be seen as the following image:

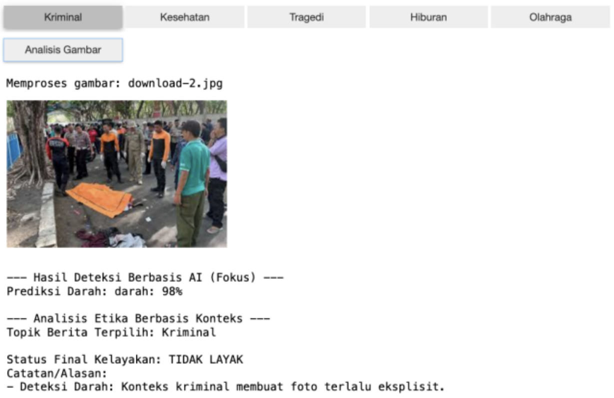


Figure 3. Results of the blood stain detection model

The image with the blood-like image detection feature explains the process by which the system automatically performs an in-depth analysis after uploading an image and pressing the "Process" button. In this case, the app successfully detected "Image contains 98% blood," indicating high accuracy in identifying inappropriate blood elements in an image.

The model is also trained to recognize facial expressions that indicate distress, such as tears, distorted faces, or expressions of pain. The goal of this detection is to identify potential emotional exploitation or sensationalism in news reports. Similar to blood detection, the results of distress expression detection will be tailored to the context. For example, a photo of distress in entertainment news (e.g., a public figure crying) will be deemed inappropriate due to a violation of privacy, while in news of a tragedy or disaster (e.g., a disaster victim grieving) may be deemed appropriate to show the humanitarian impact of the event. The following displays the results of the CNN Model application that has been successfully created with a feature that will process image data that can be uploaded and can be seen as the following image:

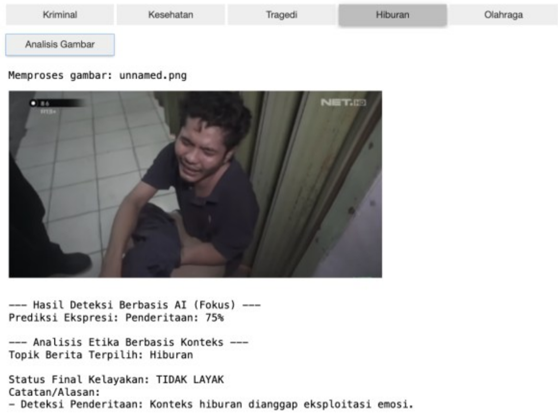


Figure 4. Results of the child's distress expression detection model

The image depicting the distress detection process illustrates the process, as after an image is uploaded and the "Process" button is pressed, the system automatically performs a thorough analysis. In this case, the application successfully detected "Image contains 75% blood," indicating high accuracy in identifying specific elements within an image.

C. CNN Model Training Results

The results of the CNN Model training obtained are as in the following table:

TABLE 4
MODEL TRAINING RESULTS

Epoch	Train Loss	Train Acc	Val Loss	Val Acc
Jan-20	227,779	4.27013889	20,045	4.45486111
Feb-20	186,069	4.61666667	186,068	4.71458333
Mar-20	176,333	0.48541667	183,202	4.72777778
Apr-20	163,609	5,12222222	179,079	4.85069444
May 20	147,005	5.37638889	155,505	5,31111111
Jun-20	130,666	5,60555556	134,272	0.55833333
Jul-20	120,555	5.74444444	139,817	5.53541667
Aug-20	114,153	5.81458333	128,598	5.66111111
Sep-20	109,029	5.87916667	125,838	5,70972222
Oct-20	10,402	5.92083333	128,497	5.68472222
Nov-20	99,919	5.97847222	128,613	5.69236111

Dec-20	96,828	6.01944444	126,681	5,71111111
13/20	93,517	6.05347222	12,219	5.78263889
14/20	90,639	6.07847222	113,708	5.87222222
15/20	87,096	6,11041667	114,468	5.84930556
16/20	84,988	6,13333333	117,615	0.58888889
17/20	82,543	6.16458333	10,342	5.97013889
18/20	80,642	6,18333333	118,753	5.89791667
19/20	78,354	6,20347222	112,547	5.93125
20/20	75,792	6.22777778	111,485	5.95069444

Based on the image of the model training results above, it shows that the model was trained in cuda. It can be concluded that the model was trained using a GPU, which speeds up the computational process. The training lasted for 20 epochs with a total dataset size of 56,078 images, of which 80% was used for training and 20% (14,018 images) for validation and testing. During each epoch, the model progressively showed an increase in accuracy (Train Acc) and a decrease in loss (Train Loss) on the training data, indicating that the model successfully learned patterns from the dataset. In addition, Val Acc (validation accuracy) and Val Loss (validation loss) also improved, indicating the model's ability to generalize knowledge to new, previously unseen data. The best model was successfully saved several times in different epochs (e.g., epochs 2, 3, 4, 5, 6, 14, and 19), indicating that the model consistently found optimal points with increasingly better validation performance. At the end of training (epoch 20), the training accuracy reached 89.68% and the validation accuracy reached 85.69%. The small difference between these two metrics indicates that your model is not experiencing significant overfitting. This indicates that the model not only memorizes the training data but is also able to generalize well to unknown data. In our final results, The integration of Grad-CAM also transforms our model from a black box into a transparent decision-support tool, providing greater confidence in the enforcement of media ethics standards. For example, the following Grad-CAM results from expression detection.

Figure 5. Results Grad-Cam

The image above shows a visualization of the interpretation of a journalistic photo predicted as "Publishable" because it contains a happy expression . This Grad-CAM result is significant because it demonstrates that the model's decision is not based on random pixels or backgrounds, but rather focuses on expression-specific features .

D. CNN Model Training Results Analysis

Test results of a developed Convolutional Neural Network (CNN)-based journalistic ethics violation detection system. Testing was conducted using a journalistic image dataset labeled based on ethical and unethical categories according to the journalistic code of ethics guidelines. Evaluation results include accuracy, precision, recall, and F1-score metrics, as well as confusion matrix visualization to understand classification performance in each category. Furthermore, the analysis also includes the system's success rate in recognizing certain types of violations such as visual violence, privacy violations, or child exploitation in images. The test data serves as the basis for discussing the effectiveness and reliability of the system in the context of its application in a media editorial environment. The following is a graph of the evaluation of the model test results:

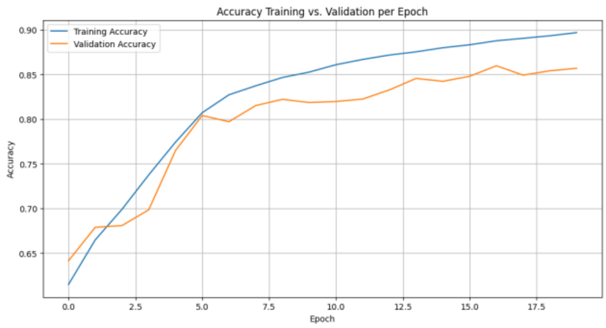


Figure 6. Training accuracy graph

Figure 11 shows a graph of the test accuracy and performance of a machine learning model during the training process, comparing the training accuracy with the validation accuracy at each epoch. The training accuracy, shown by the blue line, steadily increases over time, indicating that the model is successfully learning the training data. This steady increase is the result of the model's optimization, which continuously adjusts its weights to minimize error on datasets it repeatedly encounters. The validation accuracy, represented by the orange line, also increases initially, reflecting the model's ability to generalize its acquired knowledge to previously unseen data. However, after the 10th epoch, the validation accuracy tends to plateau or only increase slightly, while the training accuracy continues to climb rapidly. This increasing difference between the two lines is a classic indication of overfitting, where the model has learned too specifically about the training dataset and begins to lose its ability to perform well on new data. Based on the observed trend, the model performs best around epochs 10 to 12, where the validation accuracy peaks before plateauing. After this point, further training does not significantly improve model performance in the real world. To further improve validation accuracy, a more effective strategy is to apply regularization techniques (such as dropout or early stopping) or use a more diverse dataset, rather than simply continuing training.

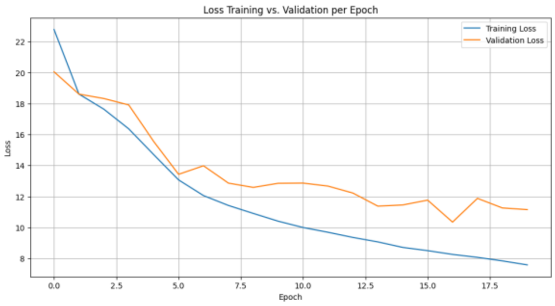


Figure 7. Model training graph

Based on the graph in Figure 12, it can be seen that the model's loss value decreases consistently throughout the training process. The blue line (Training Loss) shows the loss on the training dataset, which continues to decrease. This indicates that the model has successfully adapted well to the data used to train it. This smooth decrease reflects an effective learning process, where the model gradually reduces its error with each epoch. The orange line (Validation Loss) shows the loss on the validation data. Although its value also decreases overall, the trend is not as smooth as the training line. There are quite significant fluctuations, such as small increases around the 5th and 9th epochs. These fluctuations indicate that the model is having difficulty generalizing the knowledge gained from the training data to entirely new data. The validation loss, which continues to decrease up to a certain point, indicates that the model is still learning, but these fluctuations indicate that the performance improvement is inconsistent. Similar to the previous accuracy graph, the point where the Training Loss and Validation Loss lines begin to separate significantly is an indication of overfitting. In this graph, the difference becomes apparent after the 12th epoch, where the training loss continues to decline sharply, while the validation loss tends to plateau or even fluctuate slightly upward. This signals that the model is starting to memorize the training data and is no longer improving its ability to perform well on new data, which is the primary goal of the validation process.

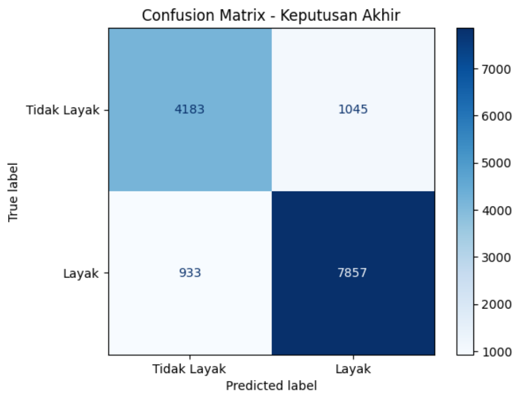


Figure 8. Confusion matrix graph

Figure 13 above shows a confusion matrix showing the model's classification results into two classes: 'Unfit' and 'Fits'. Each cell in the matrix represents the number of data predicted by the model compared to the original label. The numbers on the diagonal from top left to bottom right (4183 and 7857) are the number of correct predictions, indicating that the model correctly classified data as 'Unfit' 4,183 times and as 'Fits' 7,857 times. However, this matrix also reveals prediction errors. There were 1,045 data that should have been labeled 'Unfit' but were incorrectly predicted by the model as 'Fits' (these are False Positives). This error is very critical if the context is, for example, a product's feasibility assessment, where an unfit product actually passes. On the other hand, there were 933 data that should have been 'Fits' but were incorrectly classified as 'Unfit' (these are False Negatives), which is also a significant error, although it may be less critical depending on the application. Overall, the model performed quite well in predicting the 'Eligible' class, as the number of True Positives (7,857) was significantly higher than the number of False Negatives (933). However, the prediction accuracy for the 'Uneligible' class was slightly lower due to the large number of False Positives (1,045). To further improve the model's performance, improvements should be focused on reducing the number of such prediction errors, especially false positives, to ensure the model can more accurately distinguish between the two classes.

E. Discussion

This research builds on previous studies that examined ethical aspects of journalistic photography and the application of the Convolutional Neural Network (CNN) method for image classification in non-journalistic domains. The literature review reveals that no research has explicitly incorporated a CNN approach into analyzing the publication suitability of journalistic photos from an ethical perspective. Several studies, such as those by RP Putra (2022), focused on the ethical principles of journalistic photography without an analytical technology approach, while Rohim et al. (2019) and Arsal et al. utilized CNN in the classification of food and flower images, which are entirely different contexts. The study by Gamala and Nasution (2016) focused more on analyzing the application of codes of ethics in online media but did not integrate machine learning methods. Therefore, this study addresses a gap unexplored by previous research by combining a journalistic ethics approach and CNN technology as a tool for automatic image classification.

The results of this study indicate that the trained CNN model is capable of detecting and classifying four target objects related to ethical violations of photojournalism: bloodstains, pornography, expressions of suffering, and uncensored faces of minors. Each developed model demonstrated relatively high performance in terms of accuracy, recall, and F1-score, and produced stable training graphs between the training and validation sets. Implementation in a simple HTML-based application also successfully displayed fairly accurate detection results. This system not only assists the image feasibility analysis process but also opens up the possibility of practical applications to assist media editors in the process of curating visual content before publication.

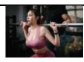
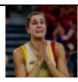
Overall, this research provides novel contributions to the application of technology-based journalistic ethics. Its strength lies in its approach, which combines visual analysis using CNNs with ethical dimensions, which have traditionally been more subjective. However, limitations were also identified, such as limited dataset variety and the lack of models specifically trained for certain expressions, such as hysterical crying, or the cultural context of images. The authors recommend further research to fine-tune the model with a broader and more contextualized dataset, and to consider developing a system that can be integrated directly into an AI-based news editorial system to automatically and real-time detect visual ethics violations. System testing was conducted to evaluate the effectiveness of the CNN model in detecting ethical violations in journalistic photos. Testing was conducted on several image datasets categorized by type of violation, including: pornography, uncensored faces of minors. Each category was tested using a CNN model that had been trained or selected from pretrained models for specific cases. Each prediction result was compiled and compared with ground truth labels to obtain accuracy, precision, recall, and F1-score values. The use of CNN-based classification models in the context of journalistic ethics decisions carries important implications regarding fairness and bias. The possibility of bias in the dataset cannot be ignored, particularly bias related to gender representation, contexts of violence, or cultural contexts that tend to be dominated by certain types of news coverage from the data source. If the training dataset disproportionately contains sensitive imagery of certain groups, the model risks learning this bias, which could ultimately lead to unfair decisions (e.g., systematically banning the publication of photos of certain subjects). To mitigate this risk, this study implemented a balanced annotation approach between classes (Eligible and Uneligible). However, as an important further mitigation step for future implementations, it is recommended to explicitly use Fairness-Aware Machine Learning techniques and conduct regular dataset audits to detect and balance any subtle biases that may be missed, thereby ensuring the ethical validity of the model.

TABLE 5
MODEL ACCURACY RESULTS

Class / Accuracy	Precision	Recall	f1-score	Support
Not feasible	0.82	0.8	0.81	5228
Worthy	0.88	0.89	0.89	8790
Macro avg	0.85	0.85	0.85	14018
Weighted average	0.86	0.86	0.86	14018

Table 2 is a classification report that summarizes the model's performance in more detail. The developed Convolutional Neural Network (CNN) model demonstrated strong effectiveness in classifying online media photojournalism ethics into "Appropriate" and "Unsuitable for Publication" categories. The test results showed a weighted average accuracy of 0.86 (86%), indicating that the model was able to correctly predict the publication suitability of photos in most cases. Furthermore, the F1-score metric, which is a harmonization of precision and recall, also reached 0.86 on a weighted average. This value indicates a good balance between the model's ability to correctly identify all positive cases (recall) and minimize false positives (precision). Specifically, the model performed very well in identifying "Appropriate" photos with accuracy, precision, and F1 - score reaching 0.88-0.89. This overall performance proves that the CNN model has successfully achieved its goal of analyzing and sorting photojournalism based on image-based publication ethics. The achievement of these high performance metrics confirms that the proposed CNN model is effective as a tool in the editing process and determining the suitability of journalistic photos in online media. With macro average values (Macro avg) for accuracy, precision, recall, and F1 - score consistently at 0.85 (85%), the model shows uniform performance for both classes ("Fair" and "Unfit"), indicating robustness in classification. The model's ability to automatically analyze images and identify potential ethical violations—where the "Unfit" class still shows strong performance at an F1 - score of 0.81—can speed up the editorial work process. Therefore, these test results convincingly support the argument that the CNN method can be used effectively as a decision support system to ensure published journalistic photos comply with ethical standards, in accordance with the research objectives of this thesis. This data provides key evaluation metrics such as Precision, Recall, F1-score, and the amount of data (Support) for each class, as well as the overall average value. Precision measures how many of the model's positive predictions are actually positive, while Recall measures how many positive data points the model successfully finds. The F1-score is a combined metric that provides an overview of the balance between Precision and Recall. Based on the data, the model performs very well for both classes. However, the model slightly outperforms the 'Eligible' class, with a Precision of 0.88 and a Recall of 0.89. This indicates that of all 'Eligible' predictions made, 88% were correct, and the model successfully found 89% of all data points that should have been 'Eligible'. Conversely, performance on the 'Uneligible' class is slightly lower, with a Precision of 0.82 and a Recall of 0.80, indicating that the model makes errors more frequently in this class. The average values at the bottom of the table provide an overview of the model's overall performance. Macro avg (0.85) is a simple average of each metric across both classes, weighting them equally. Meanwhile, Weighted avg (0.86) is a weighted average based on the amount of data in each class (Support). Since the number of 'Eligible' data (8790) is greater than 'Ineligible' (5228), the weighted average (0.86) provides a more accurate picture of the model's performance on the dataset as a whole.

TABLE 6
RESULTS OF JOURNALISTIC ETHICS VALIDATION

No	Picture	Category	Topics	CNN	Validator
1		Blood	Health	Suitable for publication	In accordance
2		Blood	Criminal	Not Suitable for Publication	In accordance
3		Blood	Tragedy	Not Suitable for Publication	In accordance
4		Blood	Criminal	Not Suitable for Publication	In accordance
5		Blood	Health	Worthy Rise	In accordance
6		Pornography	Tragedy	Not Suitable for Publication	In accordance
7		Pornography	Criminal	Not Suitable for Publication	In accordance
8		Pornography	Health	Suitable for publication	In accordance
9		Pornography	Criminal	Not Suitable for Publication	In accordance
10		Pornography	Sport	Suitable for publication	In accordance
11		Minors	Criminal	Not Suitable for Publication	In accordance
12		Minors	Criminal	Not Suitable for Publication	In accordance
13		Minors	Tragedy	Not Suitable for Publication	In accordance
14		Minors	Health	Suitable for publication	In accordance
15		Minors	Entertainment	Suitable for publication	In accordance
16		Expression of Suffering	Entertainment	Suitable for publication	In accordance
17		Expression of Suffering	Criminal	Not Suitable for Publication	In accordance
18		Expression of Suffering	Tragedy	Not Suitable for Publication	In accordance
19		Expression of Suffering	Sport	Suitable for publication	In accordance

The data in Table 3 are the results of testing a Convolutional Neural Network (CNN) model developed to analyze the ethics of image-based photojournalism. The test dataset consists of 20 images with different categories:

bloodstains, pornography, minors, and expressions of suffering. Each image was processed by the CNN model to generate a prediction as to whether the photo was suitable or unsuitable for publication. The prediction results were then validated by a professional journalist certified by the Press Council to ensure the model's decisions conformed to applicable journalistic ethics standards. Based on the test results, it can be seen that the majority of images in the categories of bloodstains, pornography, minors, and expressions of suffering were predicted by the model as unsuitable for publication. This prediction was declared appropriate by the validator, indicating that the model is able to recognize visual characteristics that potentially violate journalistic ethics. Meanwhile, there is one specific case in the bloodstain category with a health topic (row 5), where the model provided a suitable prediction, and this result was also validated accordingly.

The consistent fit between the model and validator in this table indicates that the CNN-based system performed well in classifying journalistic photos as suitable or unsuitable for publication. Accuracy was high because all predictions received a "Suitable" validation from certified journalists. Thus, the model is not only capable of visual classification but also produces decisions that align with valid journalistic practice standards according to the Press Council. Overall, this test demonstrates that integrating the CNN method with a professional validation process can be an effective approach to supporting the ethical assessment of journalistic photos in online media. With this system, the editorial process can be more objective, consistent, and efficient. Furthermore, the use of certified validators strengthens the validity of this study, as the model's prediction results were directly tested against nationally recognized journalistic competency standards.

IV. CONCLUSION

Based on the results of observations that the author has made in the analysis of journalistic photo ethics using the CNN method , it can be concluded that:

Thus, this system has proven effective in improving the quality of journalistic photo selection and ensuring that media outlets adhere to ethical principles, while reducing the potential for human error in decision-making regarding irrelevant photos of minors. This analysis shows that such photos not only violate ethics but can also have a negative psychological impact on audiences and undermine media credibility.

This research successfully developed and trained a Convolutional Neural Network (CNN)-based system. This system can automatically detect and assess journalistic photos that potentially violate ethics. The model was trained using a labeled dataset, allowing the system to distinguish between suitable and unsuitable photos for publication. This success demonstrates that machine learning technology can be an effective tool to assist editors in the photo selection process.

The evaluation showed that the developed CNN system had a high level of accuracy in assessing the suitability of photos. Implementing this system can significantly assist online media editors in screening thousands of photos more quickly and objectively. Thus, this system has proven effective in improving the quality of journalistic photo selection and ensuring that media outlets adhere to ethical principles, while reducing the potential for human error in decision-making.

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