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A Comparative Study of Deep Learning Frameworks for Prediction of Women Violence

[1] Ravindra Komte, [2] Sunil Nimbhore, [3] Bharat Naiknaware, [4] Kadri Adeeba Sajjad

[1] [2] Department of CS and IT, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar
[3] [4] Dr. G.Y. Pathrikar College of CS and IT, MGM University, Chhatrapati Sambhajinagar
Corresponding Author Email: [1] ravikomte@gmail.com, [2] drssnbamu@gmail.com,
[3] bbharat.naiknaware@gmail.com, [4] adeebakadri99@gmail.com

Abstract— **The aim of comparative study of deep learning algorithms and their frameworks is to interpret women violence and their recent need to monitor and develop the Artificial intelligence based predictive and preventive model that contributes to the issues occurring with Women's in different forms of violence, especially this research work predict the Human Trafficking, Emotional Abuse, Gender Based violence, Sexual Harassment, Intimate Partner violence, Child molestation and Harassment, Brutality and Domestic violence etc.as well as the comparative performance analysis of deep learning frameworks. The research focuses on Violence against women which effectively used tensor flow and EfficientNet techniques. These Deep Learning framework for predicting Women Violence incorporates five pre trained frameworks i.e. Residual Neural Network50 (ResNet50), Inception v3, and Visual Geometry Group (Vgg16). ResNet50 has 50 layers, Inception v3 has 48 layers and Vgg16 has 16 weighted layers, EfficientNet, MobileNetV2. The Deep learning classifiers that are used for tag based image processing and enhance the quality output for prediction of task. Tag based image Dataset consist of nine types of women violence with 944 images. The deep learning frameworks shows the result based on provided trained dataset to the pre trained frameworks. The experimental results show ResNet50 got accuracy with 72 %, Vgg16 got accuracy with 84 % and InceptionV3 got accuracy with 79 %. The highest accuracy compared with all other frameworks is of Vgg16 framework with 84 %. CNN EfficientNet with 69 % MobileNetV2 with 74 %. The hidden nature of such violence and its frequent underreporting make it a critical area for research. Recent developments in artificial intelligence offer new avenues for detecting and predicting instances of women violence through Deep Learning algorithms.**

Index Terms— Artificial Intelligence, Deep Learning, Women Violence, Inception V3, Visual Geometry Group.

I. INTRODUCTION

The study focuses on physical, sexual, and psychological violence, proposing two channels: the woman's channel based on economic dependence theory, and the partner channel based on theories of financial stress and relative resources. The findings indicate that increasing the minimum wage reduces domestic violence against women, considering direct effects and the influence of both the woman and her partner [1]. A cross-national test of the feminist theory of violence against women. Combining data from the International Crime Victims Survey (ICVS) with United Nations statistics, the findings support the theory. The findings of this study add confirmation to the argument that we need to look beyond individual level variables to understand and develop strategies for reducing violence against and fear among women [2]. Violence against women (VAW) is widespread and linked to negative public health and social outcomes. Research on VAW, however, has largely been limited to convenience samples and on variable definitions of violence, hindering our ability to fully characterize this important problem nationally and among subgroups of women [3]. Several government-sponsored victimization surveys have found women's fear of crime to be much higher than that of men even though their probability of being victimized is much lower than men's. On the basis of these results, several criminologists contend that women's fear is subjectively based. However, government surveys have not adequately examined the consequences of the physical, sexual, and psychological abuse of women by male intimates. Feminist researchers contend that these assaults greatly contribute to a generalized fear of crime that is objectively based [5]. The case study should conduct exploratory data analysis to identifykey trends and drivers of GBV in Namibia, providing valuable insights for policymakers and intervention programs. By leveraging advanced ML techniques, the case study would contribute to evidence-based decision-making, policymaking, planning, and resource allocation aimed at reducing GBV incidents in Namibia. [7]. Domestic violence against women is a prevalent in Liberia, with nearly half of women reporting physical violence. This study aims to predict women's vulnerability to domestic violence using a machine learning approach, leveraging data from the Liberian Demographic and Health Survey (LDHS) conducted in 2019–2020[8]. Gender-based crime is one of the most concerning scourges of contemporary society, and governments worldwide have invested lots of economic and human resources to foretell their occurrence and anticipate the aggressions. [9].

II. RELATED WORK

Using a population-based national sample of noninstitutionalized women ages > or =18 (n = 1,800), we conducted a telephone survey on women's experiences with 6

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types of violence, including being followed and repeatedly contacted, as well as physical and sexual assault by intimate partners and others. We calculated adult lifetime and prior year prevalence of violent experiences, examined bivariate differences in experiences among groups of women, and employed logistic regression to model the odds of adult lifetime and prior year victimization. Sixty percent of the respondents experienced at least 1 form of violence since age 18; 10% reported violence in the previous year. Adult lifetime and prior-year prevalence varied widely by types of violence, and by respondent's socio demographic characteristics. Women under age 55, those receiving public assistance, and lesbian/bisexual women were at higher risk of experiencing violence in their adult lifetimes. Women age 18-24 had increased risks of victimization in the previous year [3]. Using data from a national survey on female abuse in Canadian college/university dating relationships, this study tested and failed to support the feminist hypothesis that violence by male intimate's results in higher levels of fear. The results suggest that women reassess their feelings of fear when victimized by male intimates. In particular, places generally viewed as safe by women, their own homes, are seen as more threatening than they had been in the past [4]. This study expands on a trend to include male victims of sexual coercion in order to contrast their experiences with female victims. Results from 422 Midwestern, college students reveal a phenomenal amount of sexual coercion is occurring. This study included: intoxication, blackmail, lies, false promises, guilt, threats to end the relationships, persistent touching, being held down, detainment, threat of physical force, use of force, and use of weapon[5].Multivariate analysis of variance (MANOVA) revealed that women were more likely to experience unwanted sexual behavior when the Chi-square results reveal a pattern of coercing women into more extreme behaviors, such as intercourse, while men report coercion ending in milder behavior, such as unwanted kissing or touching[6].This study provides a machine leaning-based analytical process for predicting the occurrence of GBV to aid in early prevention strategies. It was recommended in this study that Namibia should employ various machine learning (ML) algorithms as a test case. These algorithms should be compared and evaluated for their predictive accuracy in forecasting GBV events in Namibia [7]. The seven machine learning algorithms to achieve this goal, including ANN, KNN, RF, DT, XGBoost, LightGBM, and CatBoost. Our analysis revealed that the LightGBM and RF models achieved the highest accuracy in predicting women's vulnerability to domestic violence in Liberia, with 81% and 82% accuracy rates, respectively [8]. We feed the model with data extracted from the official Spanish VioGen system and comprising more than 40,000 reports of gender violence. To evaluate the performance, two new quality measures are proposed to assess the effective police protection that a model supplies and the overload in the invested resources that it generates. To the best of our knowledge, this is the first work that achieves an effective ML-based prediction for this type of crimes against an official dataset [9].

III. METHODOLOGY

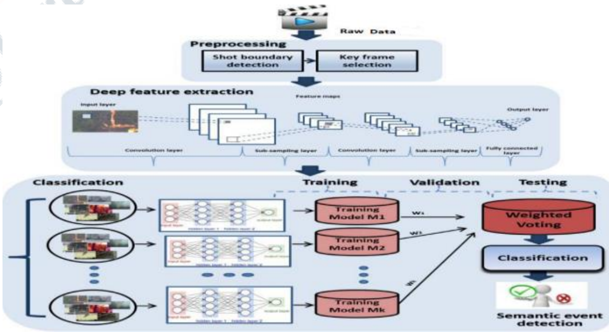
EfficientNet has played a vital role in this study where pre-trained models such as VGG16, Inception V3, and ResNet50 were utilized as a foundation for training the women violence data. The algorithms used EfficientNet to accomplish high precision while using minimal training data and processing resources.

A. Dataset:

A vast collection of approximately 944 images was initially obtained from a dataset repository called. These images encompassed in women violence types, originating from diverse sources such as web scrubbing, WHO Reports, and various imaging techniques that employed red, green, and blue (RGB) colors. A preprocessing step was executed to resize all the images to streamline the data.

B. Data Preprocessing:

The preprocessing involved a downscale procedure by specifying the desired dimensions at the input layer. Additionally, certain images were manually enhanced by augmenting their brightness. Originally, the images were of different size 256 × 256 pixels, but they were subsequently downscaled to a pixel dimension of 224 × 224. These modified images were stored in separate train and validation folders. Subsequently, the collected images were meticulously divided into different types of women violence datasets for specific purposes.



Reference- Ensemble Deep Learning framework (Samira Pouyanfar and Shu-Ching Chen, 2017, 90)

C. VGG-16

The pre-trained VGG-16 convolutional neural network model which indeed refined by freezing some of the layers to avoid Data overfitting as the case of our adopted image set which indeed is very small. The VGG-16 model is an architecture of 16 convolutional layers proposed in 2014 by Karen Simonyan and Andrew Zisserman Regarding the input image of network, it takes a form of dimensions (224 × 224 ×

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3) also it includes 16 layers of convolutional also to a fixed size filter in (3 × 3) and 5 layers of Max grouping of size (2 × 2) on the whole network.

D. ResNet50:

ResNet-50 is a convolutional neural network with 50 layers that focuses on learning residuals as opposed to features. This architecture introduces the idea of the Residual Network to address the issue of the vanishing/exploding gradient.

ResNet50 is a 50-layer residual network with 26 million parameters. Indeed, is a deep convolution neural network model introduced by Microsoft in 2015 In the residual network rather than learning features, we learn residuals which are the subtraction of learned features from the layer inputs ResNet connects the input of the nth layer directly to an (n+x)th layer, allowing additional layers to be stacked and a deep network established. We used a pre-trained ResNet50 model in our experiment and refined it.

E. Inception V3:

Inception-v3 is a 48-layer deep pre-trained convolutional neural network model, it is able to learn and recognize complex patterns and features in images. One of the key features of Inception V3 is its ability to scale to large datasets and to handle images of varying sizes and resolutions. This is important in the field of image processing, where images can vary greatly in terms of size, resolution, and quality. The weights of the classification layers were initialized using the algorithm. This approach allowed us to effectively use Inception V3 for our purposes.

F. EfficientNet:

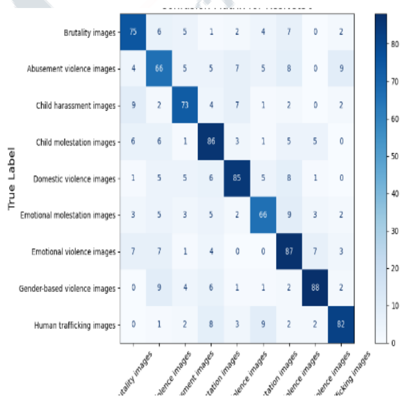
EfficientNet is a Convolutional Neural Network (CNN) architecture that utilizes a compound scaling method to uniformly scale depth, width, and resolution, providing high accuracy with computational efficiency. EfficientNet is a family of convolutional neural networks (CNNs) that aims to achieve high performance with fewer computational resources compared to previous architectures. It was introduced by Mingxing Tan and Quoc V. Le from Google Research in their 2019 paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." The core idea behind EfficientNet is a new scaling method that uniformly scales all dimensions of depth, width, and resolution using a compound coefficient. The below images show the different methods of scaling: Baseline: The original network without scaling., Width Scaling: Increasing the number of channels in each layer., Depth Scaling: Increasing the number of layers., Resolution Scaling: Increasing the input image resolution., Compound Scaling: Simultaneously increasing width, depth, and resolution according to the compound scaling formula. Evaluating the efficacy of EfficientNet involves subjecting it to various performance benchmarks and comparative analyses. Across multiple benchmark datasets and performance metrics, EfficientNet demonstrates outstanding efficiency, outperforming its predecessors in terms of accuracy, computational cost, and resource utilization [19].

G. MobileNetV2:

MobileNet V2 is a powerful and efficient convolutional neural network architecture designed for mobile and embedded vision applications. The MobileNet V2 architecture is designed to provide high performance while maintaining efficiency for mobile and embedded applications. Its innovative use of inverted residuals, linear bottlenecks, and depth wise separable convolutions make it an efficient and powerful architecture for a wide range of tasks. As mobile and embedded devices continue to evolve, MobileNet V2 will undoubtedly play a crucial role in enabling real-time, on-device AI applications [20].

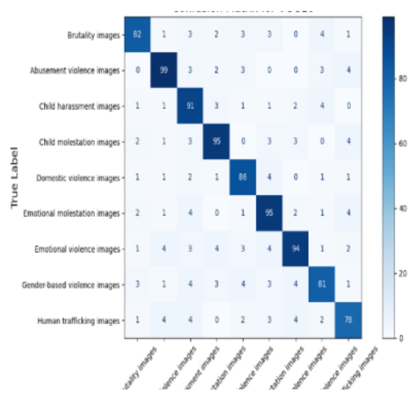
Correlation Matrix: ResNet50:

The total number of correctly detected positive instances is known as true positive (TP). True negative (TN), false positive (FP), and false negative (FN) are the percentages of false positive and false negative occurrences with ground truth, respectively, that are correctly classified as positive and negative cases.



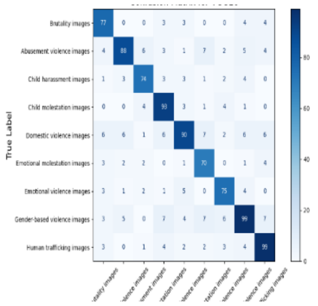
Confusion Matrix for ResNet50

Correlation Matrix: VGG16



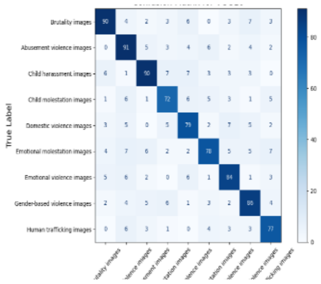
Confusion Matrix for VGG16

Correlation Matrix: InceptionV3



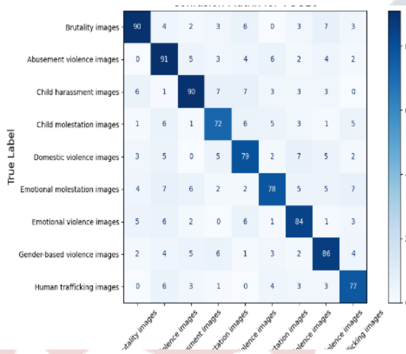
Confusion Matrix for InceptionV3

Correlation Matrix: MobileNetV2



Confusion Matrix for MobilenetV2

Correlation Matrix: CNN-EfficientNet



Confusion Matrix for CNN- EfficientNet

H. Performance metrics:

Performance metrics are used to evaluate the overall performance of Deep learning algorithms and to understand how well our Deep learning models are performing on a given data under different scenarios.

I. Confusion Matrix.

A confusion matrix is used to evaluate the performance of classification algorithms. Columns are the predicted classes, and rows are the actual classes. Now let's look at each block of our confusion matrix [18]:

1) **True Positives (TP):** In this case, the actual value is 1 and the value predicted by our classifier is also 1
2) **True Negatives (TN):** In this case, the actual value is 0 and the value predicted by our classifier is also 0
3) **False Positives (FP)**: In this case, the actual value is 0 but the value predicted by our classifier is 1
4) **False Negatives (FN):** In this case, the actual value is 1 but the value predicted by our classifier is 0

	Predicted (0)	Predicted (1)
Actual (0)	True Negatives (TN)	False Positives (FP) Type 1 error
Actual (1)	False Negatives (FN) Type 2 error	True Positives (TP)

J. Precision:

Precision can be defined as the number of correct positive predictions divided by the sum of correct positive predictions and incorrect negative predictions. The precision value ranges from 0 to 1. Precision value can be calculated from the confusion matrix using the below formula.

$$Precision = \frac{\sum True\ Positive}{\sum True\ Positive + \sum False\ Positive}$$

K. Recall: Recall or sensitivity.

Recall can be defined as the number of correct positive predictions divided by the sum of correct positive predictions and incorrect positive predictions; it is also called a true positive rate. The recall value ranges from 0 to 1.

Recall can be calculated from the confusion matrix using the below formula. The recall metric is used when the classes are imbalanced.

$$Recall = \frac{\sum True\ Positive}{\sum True\ Positive + \sum False\ Negative}$$

L. F1Score:

F1-score uses both precision and recall values. It is the harmonic mean of Precision and recall score. F1-score gives a balance between Precision and recall. It works best when the precision and recall scores are balanced. we always want our classifiers to have high precision and recall but there is always a trade-off between precision and recall when tuning the classifier. The F1-score can be calculated using the below formula.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

M. Accuracy:

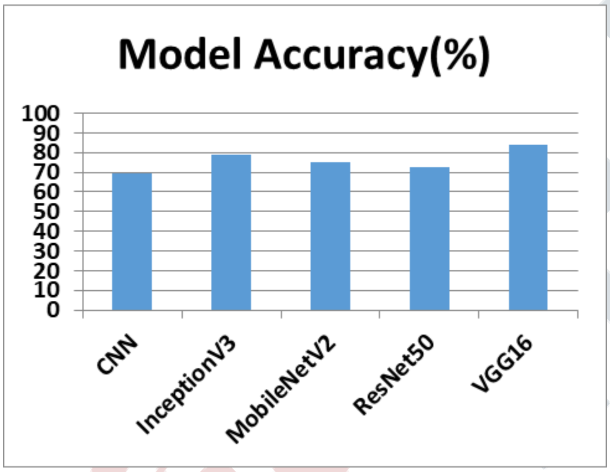
Accuracy is the most commonly used performance metric for classification algorithms. Accuracy can be defined as the number of correct predictions divided by Total predictions. We can easily calculate accuracy from the confusion matrix using the below formula.

Evaluating the performance of a deep learning model is crucial in order to determine its ability to make accurate predictions on unseen data. By assessing the model's performance, we can identify any potential limitations or issues and take steps to improve its accuracy. We assessed our model's performance using accuracy graphs as described in below [18]

$$Accuracy = \frac{\text{Number of Correct predictions}\left(\sum \text{True Positive} + \sum \text{True Negative}\right)}{\text{Total Population}\left(\sum \text{True Positive} + \sum \text{True Negative} + \sum \text{False Positive} + \sum \text{False Negative}\right)}$$

Table I: Comparative Deep Learning Framework Analysis:

Sr. No.	Framework	Precision	Recall	F1-Score	Accuracy
1	CNN-EfficientNet	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



Deep Learning frameworks for predicting Women Violence incorporates five pre trained frameworks i.e. Residual Neural Network50 (ResNet50), Inception v3, and Visual Geometry Group (Vgg16). ResNet50 has 50 layers, Inception v3 has 48 layers and Vgg16 has 16 weighted layers. The Deep learning classifiers that are used for tag-based image processing and enhance the quality output for prediction of task. Tag based image Dataset consist of nine types of women violence with 944 images. The deep learning frameworks shows the result based on provided trained dataset to the pre trained frameworks. The experimental results show ResNet50 got accuracy with 72 %, Vgg16 got accuracy with 84 % and InceptionV3 got accuracy with 79 %. The highest accuracy compared with all other frameworks is of Vgg16 framework with 84 %. CNN EfficientNet with 69 % MobileNetV2 with 74 %.

IV. CONCLUSION

The findings of our study demonstrate that Deep Learning frameworks have high accuracy rates in determining the frequency and risk factors of violence against women, indicating that they can be used safely.

This study analyzed Women violence using various Deep Learning classifiers, including ResNet connection skipping, Inception V3, VGG 16, ResNet50, EfficientNet and MobileNetV2 For the training and testing stages, we utilized Python version 3.7 and employed the Tensorflow preprocess function on Google Colab.

The Deep Learning frameworks performed and computed the best accuracy ResNet50 accuracy 72% VGG16 accuracy 84% InceptionV3 accuracy 79%, EfficientNet69% and MobileNetV2 74%

The Vgg16 having best deep learning framework with 84% Accuracy.

Deep Learning frameworks are computationally very high end data process and analyzed that helps to predict the tag based image and women violences correctly.

This research work predict types of women violence like Human Trafficking, Emotional Abuse, Gender Based violence, Sexual Harassment, Intimate Partner violence, Child molestation and Harassment, Brutality and Domestic violence etc.

REFERENCES

[1] Agüero JM, Frisancho V. Measuring violence against women with experimental methods. Econ Dev Cult Change. 2022;70(4):1565-1590. doi:10.1086/714008

[2] Bükecik E, Özkan B. Violence against women: the impact of gender inequality on women's health. İzmir Katip Çelebi Univ Fac Health Sci J. 2018;3(2):33-37.

[3] Moracco KE, Runyan CW, Bowling JM, Earp JA. Women's experiences with violence: a national study. Womens Health Issues. 2007 Jan-Feb;17(1):3-12. doi: 10.1016/j.whi.2006.03.007. PMID: 17321942.

[4] Kelly KD, DeKeseredy WS. Women's fear of crime and abuse in college and university dating relationships. Violence Vict. 1994 Spring;9(1):17-30. PMID: 7826932.

[5] Chavez, Carlos. "Domestic Violence, Labor Market, and Minimum Wage: Theory and Evidence" Review of Economics, vol. 74, no. 3, 2023, pp. 195-233. https://doi.org/10.1515/roe-2023-0013Chavez, Carlos. "Domestic Violence, Labor Market, and Minimum Wage: Theory and Evidence" Review of Economics, vol. 74, no. 3, 2023, pp. 195-233. https://doi.org/10.1515/roe-2023-0013

[6] Waldner-Haugrud LK, Magruder B. Male and female sexual victimization in dating relationships: gender

differences in coercion techniques and outcomes. Violence Vict. 1995 Fall;10(3):203-15. PMID: 8777187.

[7] P. P. Shifidi, C. Stanley and A. A. Azeta, "Machine Learning-Based Analytical Process for Predicting the Occurrence of Gender-Based Violence," 2023 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC), Windhoek, Namibia, 2023, pp. 1-8, doi: 10.1109/ ETNCC59188.2023.10284965.

[8] Rahman, R., Khan, M.N.A., Sara, S.S. et al. A comparative study of machine learning algorithms for predicting domestic violence vulnerability in Liberian women. BMC Women's Health 23, 542 (2023). https://doi.org/10.1186/s12905-023-02701-9

[9] Ángel González-Prieto, Antonio Brú, Juan Carlos Nuño, José Luis González-Álvarez, Hybrid machine learning methods for risk assessment in gender-based crime, Knowledge-Based Systems, Volume 260, 2023, 110130, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2022.110130.

[10] Samira Pouyanfar* and Shu-Ching Chen† Automatic Video Event Detection for Imbalance Data Using Enhanced Ensemble Deep Learning International Journal of Semantic Computing Vol. 11, No. 1 (2017) 85–109 °c World Scienti¯c Publishing Company DOI: 10.1142/S1793351X17400050

[11] P. S. Sowmika, S. S. N. Rao and S. Rafi, "Machine Learning Framework for Women Safety Prediction using Decision Tree," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 1089-1093, doi: 10.1109/ICSSIT55814.2023.10060997.

[12] B. Kaur, L. Ahuja and V. Kumar, "Crime Against Women: Analysis and Prediction Using Data Mining Techniques," 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 2019, pp. 194-196, doi: 10.1109/COMITCon.2019.8862195.

[13] M. R. Reza, F. M. B. Mannan, D. Barua, S. Islam, N. I. Khan and S. R. Mahmud, "Developing a Machine Learning Based Support System for Mitigating the Suppression Against Women and Children," 2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ICEEICT53905.2021.9667924.

[14] MeysamSalehi, ShahrbanooGhahari, Mehdi Hosseinzadeh, Leila Ghalichi, Domestic violence risk prediction in Iran using a machine learning approach by analyzing Persian textual content in social media, Heliyon, Volume 9, Issue 5, 2023, e15667, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2023.e15667

[15] Nemias Saboya, A. Angel Sullon, and Omar L. Loaiza. 2020. Predictive Model Based on Machine Learning for the Detection of Physically Mistreated Women in the Peruvian Scope. In Proceedings of the 3rd International Conference on Advances in Artificial Intelligence (ICAAI '19). Association for Computing Machinery, New York, NY, USA, 18–23. https://doi.org/10.1145/3369114.3369143

[16] Sharmistha Ghosh, Soumyabrata Saha, Suparna DasGupta, and Sudarshan Nath. 2024. Machine Learning Based Approach for Crime Analysis in India with an Emphasis on Women Safety. In Computer Information Systems and Industrial Management: 23rd International Conference, CISIM 2024, Bialystok, Poland, September 27–29, 2024, Proceedings. Springer-Verlag, Berlin, Heidelberg, 229–245. https://doi.org/10.1007/978-3-031-71115-2_16

[17] Alzubaidi, L., Zhang, J., Humaidi, A.J. et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data 8, 53 (2021). https://doi.org/10.1186/s40537-021-00444-8

[18] https://medium.com/analytics-vidhya/understanding-performance-metrics-for-machine-learning-algorithms-996dd7efde1e

[19] Abdelrahman A and Viriri S (2023) EcientNet family U-Net models for deep learning semantic segmentation of kidney tumors on CT images. Front. Comput. Sci. 5:1235622. doi: 10.3389/fcomp.2023.1235622

[20] Mehdhar S.A.M. Al-Gaashani, WenboXu, EfremYohannesObsie, MobileNetV2-based deep learning architecture with progressive transfer learning for accurate monkeypox detection, Applied Soft Computing,Volume 169,2025,112553,ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2024.112553.