

Tag based Women Violence Prediction System using Deep Learning Techniques

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Abstract— In this Research article women violence Prediction system using Deep Learning Techniques to do novel approach for prediction of women violence. Now a day women violence increased day by day and it need to monitor the ratio of women violence in specific type of violence. This research article helps to predict the various types of women violence happens in throughout the globe. A system which is designed to predict specific category of women violence through the deep learning techniques. Convolution Neural network, Transfer Learning and MobileNetV2 algorithms used for women violence prediction. The model predict the Human Trafficking, Emotional Abuse, Gender Based violence, Sexual Harassment, Intimate Partner violence, Child molestation and Harassment, Brutality and Domestic violence etc. In this research article, tag based image retrieving technique used for 944 image dataset. Dataset consists of 9 category images that show the prediction of violence. Each women violence processed 105 tag based images approximately for prediction. With the help of this research one can easily predict the trend of women violence and take decision to minimize women violence rate. Preprocessing steps need for shaping the images uniquely, rescale the size of image, image annotation and clustering. Model building is the important process which needs creation of feature set and applying the method for tag based image classification. The experimental results of CNN model shows accuracy of 76% and transfer model shows the 75%. MobileNetV2 algorithms helps for device-based data processing and easy access the content that helps to user they can easily predict the women violence. This research article help to use the image datasets for women violence prediction to researcher sand studies prominent methods applied in deep learning algorithms to predict women violence.

Index Term: Deep Learning, Convolution Neural network, Transfer Learning, Gender-Based Violence.

I. INTRODUCTION

In this research article author works on violence against women is a key social issue which poses a challenge in terms of prevention, legal action and reporting the abuse once it has occurred. However, a significant number of female victims who file a complaint against their abuser and initiate legal proceedings. Research in this field has been focusing on identifying the factors underlying women victims' decision to disengage from the legal process to enable intervention before this occurs. Previous studies have applied statistical models to use input variables and make a prediction of withdrawal.

However, none have used deep learning models to predict women violence. This could represent a more accurate way of detecting these events[1].

Women Violence is a critical issue for whole community so it need to solve by all means. To overcome this there is a necessity to minimize resources for understanding and analyzing the problem to avoid past and future incidence. There is increase for using concept of Machine Learning techniques and big data worldwide for collecting the data of women violence. In this research work, creation of data collection from various websites has been done. The collected data is having various noises and so it need to preprocess. Specifically works on data annotation and feature selection for better prediction using deep learning classifiers.

Machine Learning is part of Artificial Intelligence (AI) which provides knowledge based techniques with the capability to automatically study and improve from prediction. Deep Learning classifiers are able to extract information from image data and then, after a learning phase, to develop a pattern. Diagnosis, analysis, and prediction are among the possible applications, from raw data can be utilized to form new knowledge [2].

The goal of this stage is to predict the relevance of image annotation tags and, then based on these correlation predictions, annotate images by ranking the tags of a given image, or achieve keyword-based retrieval by ranking images with a given tag. The deep Learning Classifiers proposed in this article is based on the weighted nearest neighbor method that is, the annotation of the training image is propagated to the new image [3].

II. LITERATURE SURVEY

Domestic violence against women is a prevalent issue in Liberia, with nearly half of women reporting physical violence. However, research on the biosocial factors contributing to this issue remains limited. In this study, we aim 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. To achieve this goal, we employed seven different machine learning algorithms, 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 accuracy rates of 81% and 82%, respectively. One of the key features identified across multiple algorithms was the number of people who had experienced emotional violence [3]. This paper implements deep learning as a method for automatic identification of violence victims in acute need. Experimental proof on a ground truth data set has got a correctness of up to 94%, which outperforms machine-learning systems. The study of useful features helps to classify significant words which might show acute posts in the classification process [4]. A Deep Learning approach has been proposed using Convolution Neural Network and bi-directional LSTM (CRNN) to classify three types of violence present in both text and video data, thereby making the internet a safer space for individuals. The proposed approach utilizes two datasets consisting of 400 and 600 samples each for videos and text, respectively, to evaluate more better of precision and accuracy of the model. The use of a Convolution Recurrent Neural Network framework combined with LSTM layers has resulted in an accuracy of 97% on text and 96% on videos, surpassing the performance of existing RNN models. The CRNN-based approach presents a promising solution to the problem of gender-based violence detection, with the potential to significantly improve the safety of individuals online. The role of machine learning and deep learning, we can contribute towards creating a safer and more equitable world for all. [5].

COVID-19 is now the most devastating global epidemic recorded in recent times, resulting in the deaths of up to 75-200 million people in Eurasia and North Africa, reaching a peak around 1347 to 1351 in Europe. But if we equate COVID-19 to the Black Death, it won't be quite different.

During December 2019, COVID-19 spread from Wuhan, China, and accidents and mortality grew dramatically around the world. Not only economic, emotional, medical, but also social problems such as family violence are faced by Bangladesh. Due to family violence, records of too many suicide cases, violent events, female and child torture are reported.

This research presents a customized forecast of women violence during the COVID-19 outbreak using Machine Learning Techniques. In this research article have applied Random Forest, Logistic Regression, and Naive Bayes machine learning classifiers to predict family violence and discovered the feature importance. The deep learning classifiers are evaluated based on accuracy, precision, recall, and F-score.

We have employed an oversampling strategy named synthetic minority oversampling technique (SMOTE) to solve the imbalance problem of our data. Even, we have tried to compare three machine learning model performances before and after balancing of normalization data. Finally, ROC analyses and confusion matrices were developed and analyzed by using data augmentation. Our proposed system with the random forest classifier performed better with 77% accuracy in comparison with other two machine learning classifiers[6].

III. METHODOLOGY

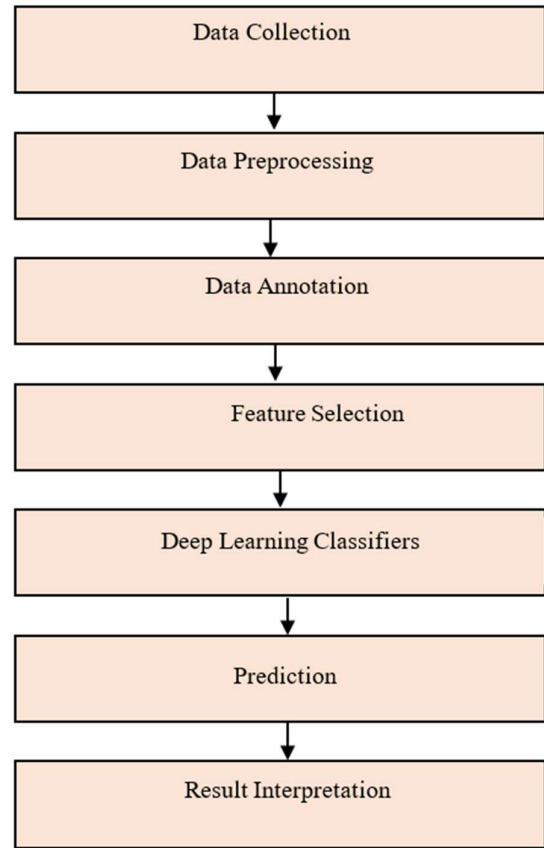


Fig.1.Methodology women violence Prediction system using Deep Learning Techniques

IV. DATA COLLECTION

Data collection is important task in women violence prediction. Data collected from various online platforms and standardized it using data preprocessing techniques. Data collection carries the various women violence category and it used for further processing. The collected Data having Human Trafficking, Emotional Abuse, Gender Based violence, Sexual Harassment, Intimate Partner violence, Child molestation and Harassment, Brutality and Domestic violence etc. Type of violence uniquely identified for studying the prediction of women violence and it is helpful for taking appropriate decision to reduce the women violence.

V. DATA PREPROCESSING

Digital images are broadly made up of pixels, which are tiny boxes representing the color and brightness values at that point in the image. Image processing involves handling these pixels in a desired manner to achieve what is required for the image. Most of the common operations performed on a digital image include filtering, enhancement, restoration, etc. In tag based image preprocessing the reshaping and resizing and prepare the unique sizes of tagged image for better result.

VI. DATA ANNOTATION

In this research article Automatic image annotation is a very important for data standardization, and its goal is to obtain relevant tag based image that can predict category of Women violence. The prediction of these keywords can be used to provide tags for images or to provide images for tags or tag combinations. Retrieval models based on image annotations and keywords [3].

VII. FEATURE SELECTION

In this Women Violence processed dataset with Tag based image input features, the feature selection process brings about Image features to predict the category of Women Violence. This results in quicker Deep Learning algorithm training, the reducing of a model's complexity so it is simpler to better prediction of Women Violence.

VIII. DEEP LEARNING CLASSIFIERS

Deep Learning is high end data processing technique it is used in this research article and predicts the outcome. In deep learning is computational model predicts to perform data classification tasks from images. Deep learning computational model show better accuracy, sometimes exceeding human-level performance. Computational Models are trained by using a large set of Image data and Deep Learning architectures that contain many layers. Deep learning classifiers are trained and tested using complex datasets of structured data and neural network architectures that learn features directly from the data without the need for manual feature extraction.

A. Convolution Neural Networks

A Convolutional Neural Network (CNN), is deep learning model used Pattern Classification and object Recognition, and high end graphical data processing. The CNN works by extracting features directly from images. The standard Training and testing ration mentioned as 70:30. This is helpful for feature selection makes deep learning classifiers most accurate for women violence recognition with various features. CNNs learn to detect different features of an image using tens or hundreds of hidden layers. Every hidden layer increases the complexity of the learned image features. For example, the first hidden layer could learn how to detect edges, and the last learns how to detect more complex shapes specifically catered to the shape of the object we are trying to recognize. The mathematical concepts behind Convolutional Neural Networks (CNNs) are fundamental to understanding how CNNs process and learn from images. CNNs are composed of various layers, and the core mathematical operations involved are convolution, pooling, activation functions, and fully connected layers.

Convolution Operation:

The convolution operation is at the heart of CNNs. It involves a mathematical operation between the input image and a set of learnable filters (also known as kernels). The purpose of convolution is to extract features from the input image. The mathematical formula for the 2D convolution operation can be expressed as:

$$[(I * K)(i, j) = \sum_m \sum_n I(i + m, j + n) * K(m, n)]$$

- (I) represents the input image.

- (K) represents the convolutional kernel.

- $((I * K)(i, j))$ is the result of the convolution at position $((i, j))$.

- $(\sum_m)$ and $(\sum_n)$ denote summation over all possible values of (m) and (n) to compute the weighted sum.

The convolution operation slides the kernel over the input image, element-wise multiplies the kernel and the portion of the image it covers, and then sums up the results. This process helps identify patterns, edges, and other features in the image.

Pooling Operation:

Pooling layers reduce the spatial dimensions of feature maps by selecting the maximum (Max-Pooling) or average (Average-Pooling) values in small regions. The mathematical formula for Max-Pooling, for example, is:

$[\text{Max-Pooling}(x, y) = \max_{\{i,j\}} (I(x + i, y + j))]$. This operation reduces the size of feature maps while retaining important information and making the network more computationally efficient.

Activation Functions:

Activation functions introduce non-linearity into the network. Common activation functions include ReLU (Rectified Linear Unit), Sigmoid, and Tanh. The ReLU activation function, for example, is defined as:

$[\text{ReLU}(x) = \max(0, x)]$. It replaces all negative values with zero, allowing the network to learn non-linear relationships in the data.

Fully Connected Layers:

After several convolutional and pooling layers, CNNs often use one or more fully connected layers for the final classification or regression tasks. These layers connect every neuron to every neuron in the previous and subsequent layers, and they use weighted sums. Mathematically, the output generated is as follows:

$$[y = \text{Activation}(\sum_{i=1}^N w_{ix_i} + b)]$$

- (y) is the output.

- (w_i) are the weights.
- (x_i) are the inputs.
- (b) is the bias term.
- Activation is an activation function.

The combination of these mathematical operations allows CNNs to learn hierarchical features from input images, making them particularly effective for tasks like image classification, object detection, and image segmentation. As the network is trained on a dataset, the learned weights in the convolutional and fully connected layers adapt to recognize specific features and patterns relevant to the task at hand.

In tag based image recognition solve discrete function of a 2D space, denoted as $f(x, y)$. Assuming the existence of a 2D convolution function $g(x, y)$, the output image $z(x, y)$ can be represented by the following formula[7]:

$$z(x, y) = f(x, y) * g(x, y)$$

Convolution Neural Networks (CNNs) are fundamental to understanding how CNNs process and learn from images. CNNs are composed of various layers, and the core mathematical operations involved are convolution, pooling, activation functions, and fully connected layers. CNN helps for Convolution Operation, Pooling Operation, Activation Functions, Fully Connected Layers etc.

B. Transfer Learning Classification:

Transfer learning and MobileNetV2 involve several mathematical concepts. Let's explore the mathematical foundations of these two topics:

Transfer Learning:

- Feature Extraction: In transfer learning, a pre-trained model is typically used as a feature extractor. The mathematical concept here involves the weights of the pre-trained model, which represent learned features from a large dataset. These features are used as a starting point for a new task.
- Fine-Tuning: Fine-tuning is the process of training the pre-trained model on a new dataset for the specific task. The mathematical concept involves updating the model's weights through back propagation and gradient descent to adapt to the new data. The learning rate, a hyperparameter, determines the step size for weight updates and plays a crucial role in fine-tuning.
- Loss Function: The loss function, often categorical cross-entropy for classification tasks, is Confusion matrix computes the predicted class and actual class for model evaluation Mathematically, it quantifies the model's performance.
- Gradient Descent: Gradient descent is a fundamental mathematical optimization algorithm used to minimize the loss function. The gradients of the loss with respect to the model's parameters are computed, and the model's weights are updated in the direction that reduces the loss. Learning rates and step sizes are important mathematical concepts here.

C. Mobilenetv2 Classification:

- Convolution Layers: MobileNetV2, like many CNNs, relies heavily on convolution layers. These layers apply mathematical convolution operations to extract features from the input data. Convolution involves element-wise multiplication and summation operations, mathematically represented as:
$$(I * K)(i, j) = \sum_m \sum_n I(i + m, j + n) * K(m, n)$$
- Depth wise Separable Convolution: MobileNetV2 introduces depth wise separable convolution, a computationally efficient variant of standard convolution. It consists of two steps: depth wise convolution (spatial convolution for each input channel separately) and pointwise convolution (combining the outputs from the depth wise step with linear combinations). This approach significantly reduces the number of mathematical operations, making it faster and more efficient.
- Global Average Pooling (GAP): MobileNetV2 employs Global Average Pooling (GAP) to reduce the spatial dimensions of feature maps. This operation involves calculating the average value for each feature map, mathematically represented as:
$$\text{GAP}(x, y) = \frac{1}{m \cdot n} \sum_{i=1}^m \sum_{j=1}^n I(x + i, y + j)$$
- Activation Functions: MobileNetV2, like other neural networks, uses activation functions (e.g., ReLU) to introduce non-linearity. The ReLU activation function is mathematically defined as:
$$\text{ReLU}(x) = \max(0, x)$$

- **Model Architecture:** MobileNetV2 has a specific architectural design, including the stacking of multiple layers. The mathematical concept involves the combination of operations, such as convolution, depth wise separable convolution, and pointwise convolution, in a structured manner to extract hierarchical features from the input data.
- **Learned Weights:** The mathematical basis of MobileNetV2 is in the learned weights during training. These weights represent the features that the model has learned to recognize in data. MobileNetV2 is pre-trained on a complex dataset and then fine-tuned for specific tasks using these learned features. Transfer learning leverages mathematical concepts related to optimization and loss functions to adapt a pre-trained model to a new task. MobileNetV2, on the other hand, involves mathematical operations related to convolution, depth wise separable convolution, and pooling to efficiently process and extract features from input data. These mathematical foundations underlie the functionality of both transfer learning and MobileNetV2.

Prediction:

This research article helps to predict the various types of women violence happens in throughout the globe. A system which is designed, to predict specific category of women violence through the deep learning techniques. Convolution Neural network, Transfer Learning and MobileNetV2 algorithms used for women violence prediction. The model predict the Human Trafficking, Emotional Abuse, Gender Based violence, Sexual Harassment, Intimate Partner violence, Child molestation and Harassment, Brutality and Domestic violence etc.

Dataset Type	Women 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
Sexual Violence(Rape)		.jpeg 260*194 5.67 KB
Sexual Harassment		.jpeg 275*183 8.21 KB
Human Trafficking		.jpeg 298*169 5.17 KB

IX. RESULT INTERPRETATION

The experimental results of CNN model shows accuracy of 76% and transfer model shows the 75%. MobileNetV2 algorithms helps for device based data processing and easy access the content that helps to user they can easily predict the women violence. This research article helps to use the image datasets for women violence prediction to researchers and studies prominent methods applied in deep learning algorithms to predict women violence.

X. CONCLUSION

In this research article, tag based image retrieving technique used for 944 image dataset. Dataset consists of 9 category images that show the prediction of violence. Each women violence processed 105 tag based images approximately for prediction. With help of this research one can easily predict the trend of women violence and take decision to minimize women violence rate. Preprocessing steps need for shaping the images uniquely,

rescale the size of image, image annotation and clustering. Model building is the important process which needs creation of feature set and applying the method for tag based image classification. The experimental results of CNN model shows accuracy of 76% and transfer model shows the 75%. MobileNetV2 algorithms

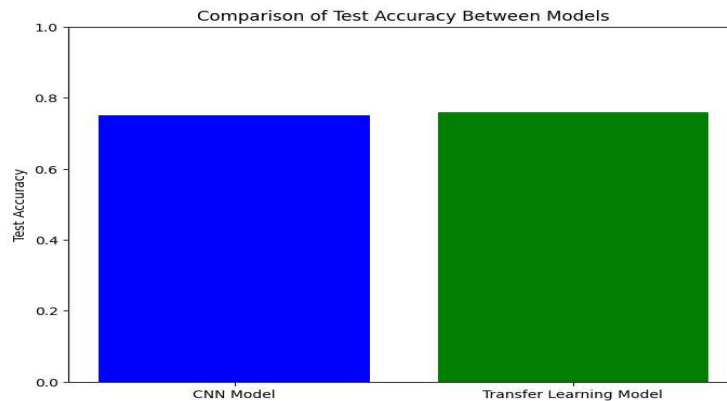


Figure 2

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