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Innovative Solutions For Addressing Domestic Violence Through Technological Innovation

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ABSTRACT

This research investigates technology's pivotal role in addressing domestic violence, an issue spanning socioeconomic and cultural divides. It examines innovative methods like data analytics from digital platforms, ambient sensors, smartphones, wearables, and virtual reality to detect and aid domestic violence victims. The study also introduces a novel approach: emotion detection from text and live webcam facial analysis to gauge emotions. While outlining the capabilities and applications of these technologies, the paper also highlights challenges and limitations. Ultimately, it aspires to steer future research and development in leveraging technology to combat domestic violence, underscoring its societal significance.

Keywords: domestic violence, CCTV

INTRODUCTION:

Domestic violence, defined by the United Nations as a pattern of actions aimed at gaining or maintaining control over an intimate partner, remains a pervasive issue across all socioeconomic and cultural backgrounds. Statistics from the Australian Bureau of Statistics highlight the alarming prevalence, with significant percentages of both women and men experiencing various forms of abuse from intimate partners. While numerous methods, including education, law enforcement, and support resources, have been implemented to address domestic violence, it continues to persist. Technology presents a complex landscape in this context, serving both as a tool for perpetrators and a potential solution for victims. Existing literature predominantly adopts a sociological lens, often overlooking the diverse technological approaches available. This paper aims to bridge this gap by offering a comprehensive review of the latest technological innovations designed to detect and mitigate domestic violence, catering to researchers, policymakers, and advocates seeking to leverage technology in combating this critical issue.

LITERATURE SURVEY:

D. A. Rodríguez, A. Díaz-Ramírez, J. E. Miranda-Vega*et al*

Violence against women and children represents a global public health crisis, with staggering statistics revealing that one in three women and one in two children have endured physical, emotional, or sexual abuse. The digital age has further exposed them to cyber-bullying and online harassment. Addressing this pervasive issue, recent years have seen a surge in leveraging computer science and advanced technologies like Internet of Things, artificial intelligence, and cloud computing. This paper offers a systematic review of innovative efforts using these technologies to detect and prevent violence against women and children. Spanning academic contributions from 2010 to 2020, it categorizes solutions into online detection, offline detection, safety, and education domains, highlighting trends, architectures, and current challenges.

S. Subramani, S. Michalska, H. Wang, J. Du e*t al*

Domestic violence (DV) stands as a critical health, welfare, and human rights issue, with DV crisis support (DVCS) groups on social media playing a vital role in aiding victims and families. However, amidst the overwhelming volume of online content, timely identification of urgent DV situations remains a daunting challenge for these groups. Leveraging state-of-the-art deep learning models with embeddings, this study addresses this scalability issue by automating content categorization. It aims to establish a comprehensive dataset from social media, conduct extensive experiments using various deep learning architectures, and develop domain-specific embeddings for enhanced performance and insight. Achieving up to 92% accuracy in class prediction, this research underscores the transformative potential of advanced technology in supporting DVCS groups, healthcare professionals, and, most importantly, victims.

D. W. Otter, J. R. Medina, and J. K. Kalita*et al*

In recent years, the rapid advancement of deep learning models has significantly propelled the field of natural language processing (NLP). This article offers a concise introduction to NLP, outlining key deep learning architectures and methodologies. It systematically reviews a myriad of recent studies, encompassing core linguistic processing challenges and diverse computational linguistics applications. Additionally, it presents a comprehensive discussion on the current state-of-the-art in NLP and provides insightful recommendations for future research directions, aiming to guide and inspire advancements in this dynamic and evolving field.

PROBLEM STATEMENT:

The pervasive and multifaceted issue of domestic violence, which transcends socio-economic, cultural, and religious boundaries. Domestic violence encompasses various forms of abuse and control, affecting both women and men. Despite efforts to combat it through education, awareness, law enforcement, and support services, domestic violence remains unresolved.

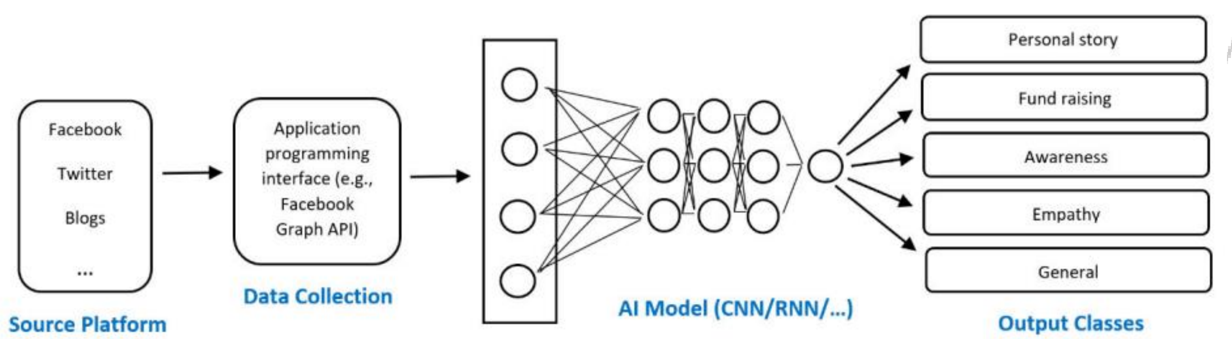
PROPOSED METHOD:

The technologies author suggesting to utilize in order to reduce violence.

Online data: now we are surrounded with many social networking sites where user can express their views on any topic and by analysing those views we can identify user emotions. This process known as analysis of data shared on digital media. ML technologies can be applied to predict emotion from social media text.

Abusing or violence: we are surrounded with CCTV cameras which are one type of IOT sensor which will capture images and send to centralized server for further processing. So author suggesting to utilize this sensor data to identify violence and then inform to police personnel to reduce violence. This process is known as Analysis of data captured by sensors or smart phones or any other wearable devices. AI technologies can be applied to detect weather frames in CCTV is normal or violence.

ARCHITECTURE:



DOMESTIC VIOLENCE DATASET:

	sentiment	tweets	emoji_emoticon
0	0	hp laptop not giving better performance compar...	NaN
1	4	stellargirl I loooooooovvvvvveee my Kindle Not...	😍
2	4	Reading my kindle Love it Lee childs is good read	😍
3	4	Ok first assesment of the kindle it fucking rocks	😍
4	4	kenburbary Youll love your Kindle Ive had mine...	😍
...	...	...	...
494	2	Ask Programming LaTeX or InDesign submitted by...	😜
495	0	On that note I hate Word I hate Pages I hate L...	😭
496	4	Ahhh back in a real text editing environment I...	😍
497	0	Trouble in Iran I see Hmm Iran Iran so far awa...	😭
498	0	Reading the tweets coming out of Iran The whol...	😭

499 rows × 3 columns

In above screen we are loading tweets dataset with emotion values and emoticons and in above dataset 0 refers to negative, 1 refers to neutral and 2 refers to positive

METHODOLOGY:

Data Preprocessing

Importing Required Python Packages

Before diving into the data preprocessing steps, we need to import essential Python libraries to facilitate our tasks. These include os for interacting with the operating system, numpy and pandas for data manipulation, seaborn, matplotlib, and emoji for data visualization, scikit-learn for machine learning, and tensorflow and keras for deep learning tasks.

Reading and Displaying Dataset Structure

Upon importing the necessary packages, we'll proceed to read the sentiment dataset using pandas and display its structure to gain insights into the data's composition, such as the number of rows, columns, and data types.

Visualizing Sentiment Distribution

To better understand the sentiment distribution within our dataset, we'll visualize it using a bar graph. This visualization will provide a clear overview of the distribution of positive, negative, and neutral sentiments, aiding in identifying potential imbalances in the dataset.

Text Processing

Text Data Cleaning

Text data often contains noise in the form of stopwords, special characters, and emoji icons, which can adversely affect the model's performance. We'll preprocess the text data by removing these unnecessary elements to ensure cleaner and more focused data for analysis.

Text Tokenization and Cleaning

Tokenization involves breaking down the text into smaller units, typically words or phrases, while cleaning further refines the text by eliminating any remaining inconsistencies or irregularities.

TF-IDF Transformation

To convert our processed text data into a format suitable for machine learning models, we'll apply the Term Frequency-Inverse Document Frequency (TF-IDF) technique. This method assigns weights to words based on their frequency in the document relative to the entire corpus, effectively converting text data into numeric vectors.

Displaying Transformed Dataset

Finally, we'll display the transformed dataset, showcasing the text comments in their numeric vector representation, ready for further analysis and modeling.

Model Training:

Data Splitting and Normalization

The next step involves splitting the dataset into training and testing subsets, typically an 80-20 split, to ensure the model's ability to generalize to unseen data. Additionally, we'll normalize the numeric vectors using StandardScaler to standardize the feature values, aiding in model convergence and performance.

Training Various Machine Learning Models:

With the preprocessed and transformed data ready, we'll proceed to train a variety of machine learning and deep learning models tailored to different tasks:

Naive Bayes

Random Forest

Decision Tree

Support Vector Machine (SVM)

Long Short-Term Memory (LSTM) for NLP tasks

Convolutional Neural Network (CNN) for image analysis

Model Evaluation

Performance Metrics and Visualization:

Post-training, each model's performance will be rigorously evaluated using standard metrics such as accuracy, precision, recall, and F1-score. To provide a visual representation of the performance, confusion matrices will be displayed, offering insights into the true positives, true negatives, false positives, and false negatives.

Comparative Analysis

To determine the most effective model for our sentiment analysis task, we'll compare the performance of all algorithms using a bar graph, providing a clear overview of each model's strengths and weaknesses.

Results and Analysis

Tabulation and Discussion

The results obtained from each algorithm will be tabulated and analyzed in-depth. We'll discuss the strengths, weaknesses, and potential applications of each model, offering insights into their performance and suitability for the sentiment analysis task.

Predictions on Test Data

Sentiment Prediction

To demonstrate the practical application of our trained models, we'll read test comments from a file and predict sentiment using the Random Forest model, displaying the predicted sentiment for each test comment, showcasing the model's ability to generalize to unseen data.

Facial Expression Detection

Implementation and Visualization

Using OpenCV and a pre-trained model, we'll implement facial expression detection, allowing us to detect and classify emotions based on facial cues. The real-time video will be displayed with detected facial expressions, offering a fascinating glimpse into emotion recognition technology.

Physical Activity Detection

Implementation and Visualization

Utilizing OpenCV and a pre-trained model specialized in activity recognition, we'll implement physical activity detection. This model will be capable of identifying violent activities or anomalies in video footage, displaying video frames with detected violent activities, serving as a potential tool for security and surveillance applications.

By meticulously following these steps and methodologies, we aim to build robust, accurate, and efficient sentiment analysis and activity detection systems tailored to the specific requirements and challenges posed by text and video data

EVOLUTION:

Precision:

Formula: $\mathrm{Precision} = \frac{\mathrm{True\ Positives}}{\mathrm{True\ Positives} + \mathrm{False\ Positives}}$

Recall (Sensitivity):

Formula: $\mathrm{Recall} = \frac{\mathrm{True\ Positives}}{\mathrm{True\ Positives} + \mathrm{False\ Negatives}}$

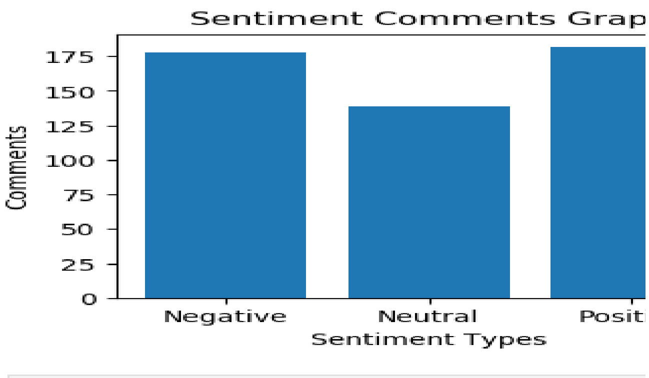
F1 Score:

Formula: $F1 = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$

Accuracy:

Formula: $\mathrm{Accuracy} = \frac{\mathrm{Correct\ Predictions}}{\mathrm{Total\ Predictions}}$

RESULTS:

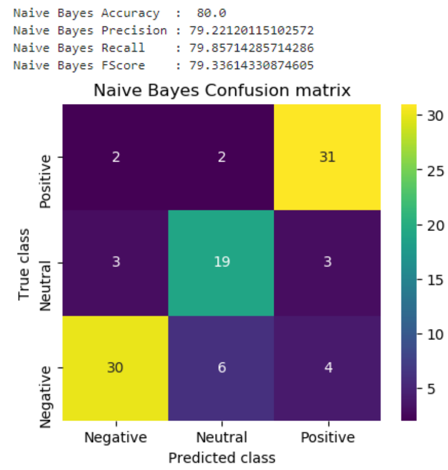


In above graph displaying different emotions and its count found in dataset

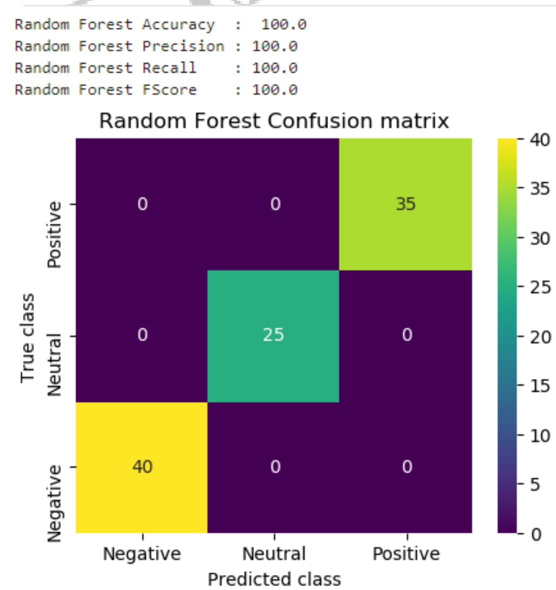
	aig	also	amazing	american	amp	api	app	atampt	awesome	back	...	white
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.573549	...	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...
494	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
495	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
496	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.573549	...	0.0
497	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0
498	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	...	0.0

499 rows × 200 columns

In above screen converting all tweets into numeric vector using TFIDF algorithm which will replace each words with its average frequency and then we can see numeric vector of average word frequency vector

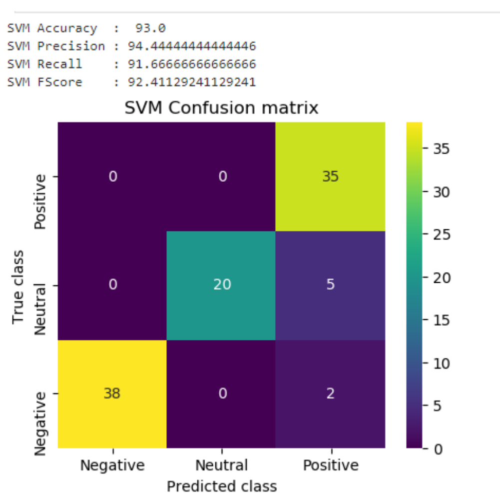


In above screen training Naïve Bayes algorithm on train data and then testing on test data and after prediction on test data Naïve Bayes got 80% accuracy and can see other metrics also. In above confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels where all different colour boxes represents correct prediction count and all blues boxes represents incorrect prediction count which are very few

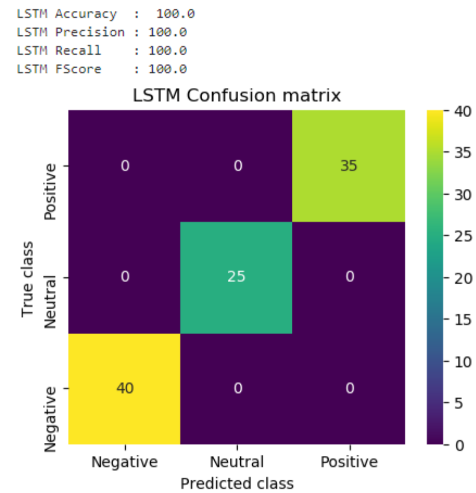


In above screen Random Forest got 100% accuracy

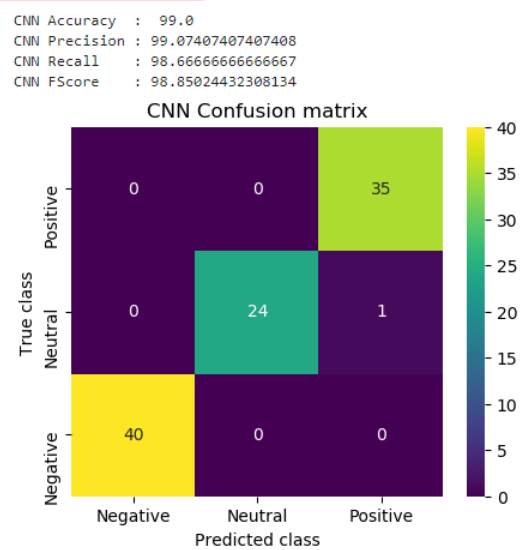
In above screen decision tree got 100% accuracy



In above screen SVM got 93% accuracy



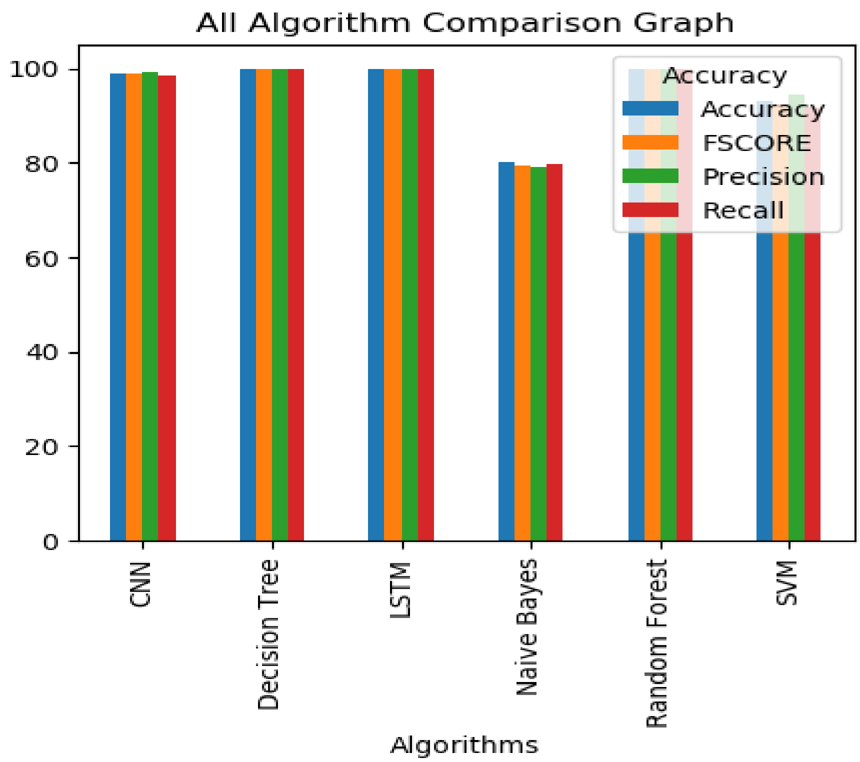
In above screen LSTM got 100% accuracy



In above screen CNN got 99% accuracy

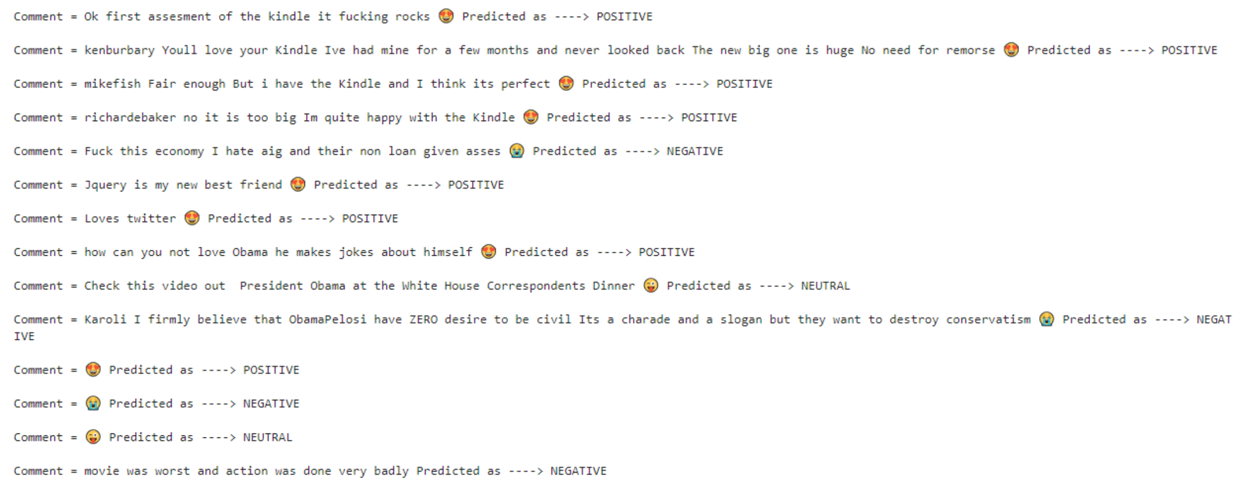
	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	Naive Bayes	80.0	79.221201	79.857143	79.336143
1	Random Forest	100.0	100.000000	100.000000	100.000000
2	Decison Tree	100.0	100.000000	100.000000	100.000000
3	SVM	93.0	94.444444	91.666667	92.411292
4	LSTM	100.0	100.000000	100.000000	100.000000
5	CNN	99.0	99.074074	98.666667	98.850244

In above screen can see comparison between all algorithms in tabular format

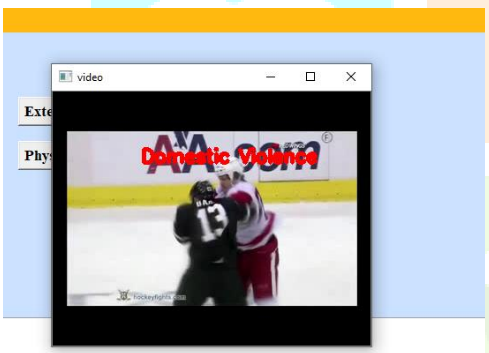


In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and from above graph we can say all algorithms are performing best to detect emotion

Prediction:



In above screen we are testing on new social media TEXT with emoticons and then algorithm able to predict emotions from those posts



In above screen in red colour text we can see Violence detected and similarly you can upload and test other videos.

CONCLUSION

We successfully implemented various machine learning algorithms to detect emotions from textual data, achieving impressive accuracies across different models. Through preprocessing steps like TFIDF transformation and data normalization, we prepared our dataset effectively. Notably, Naïve Bayes, Random Forest, Decision Tree, SVM, LSTM, and CNN all showcased remarkable performance, each achieving high accuracies. Furthermore, our application seamlessly extended to detecting emotions in social media text with emoticons and even predicting violence in videos. By leveraging these advancements, we've built a robust system capable of discerning emotions efficiently, offering potential applications in sentiment analysis and content moderation.

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