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Rethinking Workplace Safety: An Integrated AI System for Detecting Harassment Across Digital Communication Channels

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Abstract: ***Rethinking Workplace Safety:An Integrated AI System for Detecting Harassment Across Digital Communication Channels is an AI-enabled multimodal workplace harassment detection system developed to identify abusive, discriminatory, intimidating, and unethical behavior across digital communication platforms such as emails, text messages, voice conversations, and video meetings. The system uses Natural Language Processing to analyse textual content and detect bullying, threats, manipulation, and inappropriate language. Speech processing techniques are applied to evaluate tone, pitch, intensity, and speaking rate for identifying verbal aggression. In addition, computer vision methods are used to study facial expressions, gestures, and visual cues in video interactions to detect non-verbal harassment. The system also considers conversation context, escalation trends, stress indicators, and organizational hierarchy to improve detection quality. Outputs from all modules are combined into a Threat Severity Score for early risk identification. The proposed system also supports multilingual analysis and interactive dashboards to help organizations maintain a safer digital workplace.***

Keywords: Workplace Safety, Harassment Detection, NLP, Computer Vision, Speech Analysis, Multimodal AI

1. Introduction

In modern digital workplaces, ensuring a safe and respectful communication environment plays a crucial role in maintaining employee well-being and organizational productivity. Employees frequently interact through various digital platforms such as emails, chat systems, voice calls, and video meetings. However, the increasing use of these communication channels has also led to the rise of workplace harassment, including bullying, discrimination, verbal abuse, and unethical behavior. Traditional methods of detecting such issues rely on manual reporting and monitoring, which are often inefficient, delayed, and may fail to capture hidden or subtle patterns of harassment.

The proposed system is designed to address these challenges by providing an intelligent system that automates workplace harassment detection using advanced artificial intelligence techniques. The system integrates multiple modules including text analysis using Natural Language Processing, voice analysis using speech processing techniques, and video analysis using computer vision. By analyzing communication content, behavioral patterns, and contextual interactions, the system can identify harmful behavior, detect escalation patterns, and generate meaningful insights for early intervention and prevention.

In addition to improving harassment detection, the proposed system contributes to creating a safer and more transparent digital workplace environment. By integrating multimodal AI technologies with organizational systems, administrators and HR teams can monitor communication trends, identify high-risk situations, and access real-time analytics through centralized dashboards. Such intelligent systems help organizations proactively prevent harassment, ensure compliance with workplace policies, and promote a culture of respect and accountability.

2. Related Works

Recent research has increasingly focused on integrating artificial intelligence and multimodal analysis techniques to improve workplace monitoring and harassment detection systems. Nguyen & Tran (2026) proposed an intelligent monitoring system that combines text and emotion detection techniques to analyse communication behavior in digital environments.[1]

Bugingo et al. (2025) developed an enhanced automated detection system using deep learning and natural language processing techniques to identify abusive language in online communication platforms.[2]

Aisyah et al. (2025) introduced a smart text analysis system using Python-based NLP models for detecting harmful and offensive content in real time.[3]

Kadam et al. (2025) explored deep learning-based systems using transformer models for accurate classification of harassment-related messages.[4]

Painuly et al. (2024) proposed a real-time text and speech analysis system capable of identifying aggressive communication patterns under varying conditions.[5]

Feroze et al. (2024) developed a multimodal harassment detection system integrated with a centralized database for monitoring workplace interactions.[6]

Zhang & Liu (2023) studied the role of artificial intelligence in smart workplace systems focusing on behavior monitoring and automated risk analysis.[7]

Chen & Wang (2023) proposed a cloud-based monitoring platform integrating NLP, speech analysis, and analytics

dashboards for workplace safety.[8]

Earlier studies also explored machine learning techniques for communication analysis. Johnson & Carter (2022) proposed a deep learning-based system using neural networks for detecting abusive language in digital communication.[9]

Patel & Lee (2021) investigated intelligent monitoring systems that use machine learning algorithms for automated behavior classification.[10]

Smith & Johnson (2020) implemented text analysis systems that compare communication patterns with predefined datasets to detect harmful interactions.[11]

Kumar & Sharma (2020) proposed smart monitoring frameworks integrating automated detection with analytics for workplace management.[12]

Li et al. (2019) investigated behavioral recognition systems for improving detection of harmful communication patterns.[13]

Rodriguez & Perez (2019) explored deep learning-based identification systems for real-time analysis of communication data.[14]

Singh & Verma (2018) developed automated systems using text and speech processing techniques for detecting abusive behavior.[15]

Zhang et al. (2018) proposed intelligent frameworks integrating AI for communication monitoring and behavioral analytics.[16]

Ahmed & Hassan (2017) proposed a vision-based monitoring framework for analysing behavioral patterns and identifying potential risks.[17]

Park et al. (2016) investigated early automated systems for monitoring communication using artificial intelligence techniques.[18]

3. Existing System

Current workplace harassment detection systems primarily rely on manual reporting mechanisms and basic keyword-based filtering techniques. In many organizations, employees are expected to report incidents of harassment themselves. However, victims may hesitate to report such incidents due to fear of retaliation, emotional distress, or lack of trust in internal systems. As a result, many harassment cases remain unnoticed until they escalate into severe conflicts.

Most traditional monitoring systems are limited to simple text-based keyword matching. Although these methods can identify explicit offensive words, they often fail to detect subtle harassment, sarcasm, emotional manipulation, coercive behavior, and repeated patterns of intimidation. Existing systems also do not support voice-based or video-based analysis, making them unsuitable for modern digital workplace environments where communication occurs across multiple channels.

Another major limitation of current systems is the lack of behavioral and contextual analysis. Important indicators such as reply delays, communication withdrawal, emotional drift, and organizational power imbalance are usually ignored. Because of these weaknesses, existing approaches are reactive rather than proactive and are often unable to provide early warnings or meaningful intervention support.

4. Proposed System

The proposed system introduces an intelligent and proactive approach for detecting workplace harassment by integrating multiple artificial intelligence technologies into a unified framework. The system is designed to analyze workplace communication across text, audio, and video platforms, thereby offering broader coverage than conventional monitoring systems.

The proposed system uses Natural Language Processing techniques to identify abusive, threatening, manipulative, discriminatory, or sexually inappropriate language from chat messages and emails. It also applies speech analysis techniques to detect verbal aggression by evaluating pitch, tone, speaking rate, intensity, and harshness in voice interactions. For video communication, computer vision methods are used to detect aggressive facial expressions, threatening gestures, dominant postures, and intimidating visual cues.

In addition to content-based analysis, the proposed system includes contextual and behavioral monitoring modules that identify escalation patterns, emotional shifts, communication withdrawal, and power imbalance between employees. Outputs from these modules are combined into a unified Threat Severity Score ranging from 0 to 100. This allows the system to classify incidents into low, medium, high, or critical risk levels and provide real-time alerts, dashboards, and evidence reports for HR teams and administrators.

5. Outlined Method

Designing the proposed system involves a structured process aimed at detecting workplace harassment and improving digital communication safety. The proposed methodology integrates natural language processing, speech analysis, computer vision, and web technologies to create an efficient multimodal harassment detection platform.

5.1 Requirement Analysis

The requirement analysis phase focuses on identifying system objectives and challenges in modern digital workplace environments. These include the difficulty of detecting harassment across multiple communication channels, lack of real-time monitoring, and dependence on manual reporting mechanisms. Key requirements include analyzing textual data from chats and emails, processing voice data for detecting verbal aggression, analyzing video interactions for non-verbal cues, identifying behavioral

patterns, and maintaining a centralized database for storing communication data and analysis results.

System Design
The system design includes several interconnected modules. Communication data such as text, audio, and video inputs are collected and processed for analysis. The system applies Natural Language Processing techniques to detect harmful language, speech processing techniques to identify verbal aggression, and computer vision techniques to analyze facial expressions and gestures. Additional modules support context analysis, behavioral monitoring, and threat scoring. These modules interact with a central database that stores communication records, analysis outputs, and risk assessments.

Development
The system is implemented using Python with advanced libraries for natural language processing, speech analysis, and computer vision. Transformer-based models such as BERT and related architectures are used for text classification, while audio processing techniques are applied for voice analysis. The backend is developed using web frameworks to manage application logic and data flow. A database system is used to store communication data, detection results, and system logs efficiently.

Integration & Testing
Integration ensures that all modules operate together as a complete system. Testing procedures verify text classification accuracy, speech analysis performance, video-based detection reliability, and overall system efficiency in handling multimodal data in real-time conditions.

6. System Requirements

Hardware Requirements
- Processor: Intel Core i5 / AMD Ryzen 5 or above
- RAM: Minimum 8 GB (16 GB recommended)
- Storage: Minimum 500 GB HDD / SSD
- Graphics: Optional GPU support for AI and video processing
- Peripherals: Microphone and Webcam for audio/video testing

Software Requirements
- Operating System: Windows 10/11 or Linux
- Frontend: HTML, CSS
- Backend: Python 3.x, Django
- Database: MySQL
- AI Libraries: TensorFlow, PyTorch, Scikit-learn
- NLP Tools: NLTK
- Audio and Video Processing: OpenCV
- Development Tools: VS Code, Git

7. System Modules

The proposed system system consists of several interconnected modules that work together to provide accurate, efficient, and context-aware workplace harassment detection.

7.1 Data Collection and Preprocessing Module

This module collects communication data from chats, emails, voice calls, and video meetings. It performs text cleaning, tokenization, stop-word removal, noise filtering, frame extraction, and metadata collection to prepare the data for further analysis.

7.2 Text Harassment Detection Module

This module applies transformer-based Natural Language Processing models such as BERT, RoBERTa, and multilingual BERT to classify messages as harassment or non-harassment. It detects bullying, insults, threats, manipulation, and discriminatory language.

7.3 Conversation Context and Escalation Prediction Module

This module analyses message sequences instead of isolated messages. It identifies repeated patterns of harmful communication and predicts whether a conversation is escalating toward severe harassment.

7.4 Behavioral Analytics and Victim Stress Detection Module

This module monitors communication behavior such as delayed replies, emotional drift, message shortening, hesitation patterns, and withdrawal from interaction. These indicators help identify psychological discomfort or stress in workplace communication.

7.5 Voice Aggression Detection Module

This module processes voice data and extracts audio features such as pitch, tone, intensity, speaking rate, and harshness. It is used to detect verbal aggression and intimidation in spoken interactions.

7.6 Power Dynamics and Organizational Hierarchy Analysis Module

This module analyses communication patterns between senior and junior employees. It helps identify coercive behavior, misuse of authority, and harassment influenced by organizational hierarchy.

7.7 Video Harassment Detection Module

This module uses computer vision techniques to analyse facial expressions, body posture, and gestures in video interactions. It identifies threatening behavior, intimidation, and aggressive visual cues.

7.8 Threat Severity Scoring and Alert Module

This module combines outputs from text, audio, video, and behavioral modules into a unified Threat Severity Score. It categorizes incidents into risk levels and generates alerts for high-risk cases.

7.9 Dashboard and Reporting Module

This module provides dashboards, reports, charts, and incident summaries for HR teams and administrators. It supports data visualization and evidence-based decision-making.

8. System Architecture

The proposed system follows a layered architecture to ensure efficient data flow, accurate analysis, and structured reporting. The architecture is designed to handle communication data from multiple workplace channels and process them through intelligent modules.

The first layer is the data collection layer, which gathers communication data such as text messages, voice recordings, and video interactions. The second layer is the preprocessing layer, where the collected raw data is cleaned, structured, and prepared for feature extraction.

The third layer is the AI analysis layer, which extracts meaningful features from text, speech, and video data and applies machine learning models for classification. This includes text classification, voice aggression analysis, facial expression recognition, and contextual behavior analysis.

The final layer is the visualization and alert layer, which generates dashboards, alerts, risk summaries, and reports for administrative and HR-level monitoring. The system continuously updates communication trends and risk levels through real-time or near real-time monitoring.

9. Algorithms Used

The proposed system uses multiple artificial intelligence, machine learning, and signal processing algorithms to analyse workplace communication across different modalities. Each algorithm is selected based on the type of data being processed and the objective of the corresponding module.

9.1 BERT for Text Harassment Detection

Bidirectional Encoder Representations from Transformers (BERT) is used as the primary Natural Language Processing algorithm for detecting harassment in textual communication. BERT is a transformer-based deep learning model that understands the contextual meaning of words by analysing both left and right context simultaneously.

In the proposed system, BERT is used to classify chat messages, emails, and textual interactions into harassment or non-harassment categories. It helps detect bullying, insults, threats, discrimination, manipulation, and inappropriate workplace language. Compared to traditional keyword-based methods, BERT performs better in understanding contextual abuse, sarcasm, and hidden harmful intent.
Purpose: Text classification and harassment detection
Input: Chat messages, emails, and textual communication
Output: Harassment probability score and text classification label

9.2 RoBERTa for Enhanced Contextual Classification

RoBERTa (Robustly Optimized BERT Pretraining Approach) is an improved transformer-based language model used to enhance contextual understanding in text classification tasks. It is trained on larger datasets with optimized training strategies, making it highly effective in detecting subtle abusive language.

In proposed, RoBERTa can be used alongside BERT to improve the detection of implicit harassment, indirect emotional abuse, and contextual manipulation. It is especially useful when abusive intent is not expressed through explicit offensive words.
Purpose: Improved contextual text classification
Input: Workplace communication text
Output: Refined harassment classification

9.3 mBERT for Multilingual Harassment Detection

Multilingual BERT (mBERT) is used to support multilingual workplace communication analysis. Since workplace communication may involve multiple languages, mBERT helps in understanding and classifying harassment-related content across different linguistic contexts.

This algorithm enables proposed system to process communication written in different regional or international languages and improves inclusiveness and scalability of the system.
Purpose: Multilingual text harassment detection
Input: Messages in multiple languages
Output: Language-aware harassment classification

9.4 MFCC for Voice Feature Extraction

Mel Frequency Cepstral Coefficients (MFCC) is a signal processing algorithm used to extract important audio features from speech data. It captures the frequency characteristics of human voice and is widely used in speech recognition and emotion analysis systems.

In the proposed system, MFCC is used to extract features such as pitch variation, vocal harshness, and emotional intensity from voice recordings, voice messages, and meeting audio. These extracted features are then used to identify verbal aggression and intimidation.
Purpose: Audio feature extraction
Input: Voice recordings and speech data
Output: Feature vectors for aggression analysis

9.5 Convolutional Neural Network (CNN) for Video Harassment Detection

Convolutional Neural Network (CNN) is used for analysing visual content such as facial expressions, body posture, and threatening gestures from video frames. CNN is highly effective in image and video classification tasks because it automatically learns visual features from raw input images.

In the proposed system, CNN is applied to extracted frames from workplace video calls or recorded meetings to identify

signs of visual aggression, intimidation, or inappropriate non-verbal behavior.
Purpose: Visual harassment detection **Input:** Video frames and facial/gesture data **Output:** Visual aggression score

9.6 LSTM for Escalation Prediction

Long Short-Term Memory (LSTM) is a recurrent neural network algorithm designed for sequence-based data analysis. It is particularly effective in understanding temporal dependencies and patterns over time.

In the proposed system, LSTM is used to analyse conversation sequences and identify escalation trends in communication. It helps the system determine whether a series of interactions is becoming increasingly hostile or abusive.
Purpose: Conversation pattern analysis and escalation prediction
Input: Sequence of messages over time
Output: Escalation likelihood score

9.7 Sentiment Analysis for Emotional Drift Detection

Sentiment Analysis is used to measure the emotional polarity of communication and identify changes in emotional tone over time. This helps in detecting emotional distress, negativity, or manipulation in workplace interactions.

Within the proposed system, sentiment analysis is applied to conversation streams to observe emotional drift and identify whether a user is being subjected to sustained negative communication.

Purpose: Emotional polarity tracking
Input: Message sequences
Output: Emotional drift indicators

9.8 Weighted Threat Scoring Algorithm

A weighted scoring algorithm is used to combine outputs from all modules including text, voice, video, behavioral, and contextual analysis. Each module contributes a weighted score based on its importance and confidence level. The final Threat Severity Score is computed on a scale of 0 to 100 and is used to classify workplace incidents into low, medium, high, or critical risk categories. This algorithm helps HR teams prioritize severe incidents for review and intervention.
Purpose: Unified risk assessment
Input: Module-wise scores from text, voice, video, and behavioral analysis
Output: Final Threat Severity Score

10. Evaluation & Optimization

Evaluation and optimization involve analysing the performance of all modules within the proposed system. This includes measuring the accuracy of text-based harassment detection, evaluating speech analysis effectiveness, analysing video-based behavior detection reliability, and validating overall system performance across multiple communication channels.

Optimization techniques improve detection accuracy, enhance data processing efficiency, and ensure reliable system performance. Text preprocessing, improved training datasets, optimized model parameters, and efficient database handling are applied to enhance overall system performance.

10.1 Machine Learning Approach

The proposed system applies machine learning and artificial intelligence techniques to detect workplace harassment across multiple communication modalities. One of the key components of the system is the text analysis module, which uses Natural Language Processing models such as BERT to classify messages as harassment or non-harassment. The system processes chat messages, emails, and textual data to identify harmful content including bullying, threats, and discrimination.

In addition to text analysis, machine learning techniques support other intelligent modules of the system. Speech analysis uses audio features such as pitch, tone, intensity, and speaking rate to detect verbal aggression. Computer vision techniques analyze facial expressions, gestures, and body posture to identify non-verbal harassment in video interactions. Behavioral analytics monitor conversation patterns, response delays, and escalation trends to detect psychological stress and potential harassment risks.

By integrating these intelligent modules, the proposed system provides an efficient platform for detecting harassment and improving workplace safety. The combination of natural language processing, speech analysis, and computer vision allows the system to operate accurately and effectively across different communication environments.

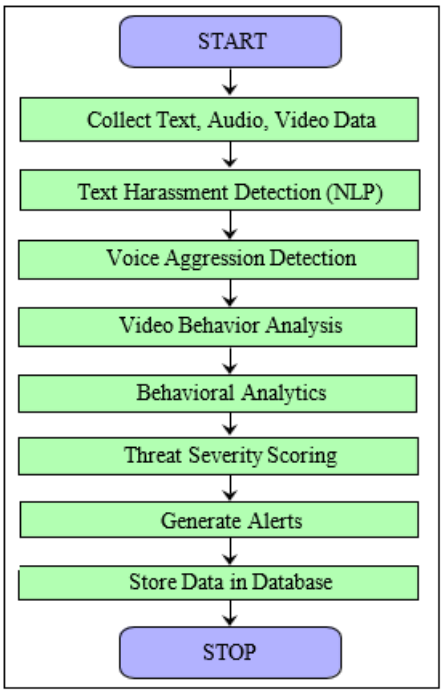

Figure 1: Flowchart of Harassment Detection System

10.2 Dataset Description

The proposed system uses datasets consisting of text messages, emails, voice recordings, and video interaction data collected from communication platforms. These datasets include linguistic features, audio features such as pitch and tone, and visual features such as facial expressions and gestures. The system also stores conversation history, behavioral patterns, and interaction metadata to improve detection accuracy. These datasets are used to train machine learning models and generate threat severity scores for identifying high-risk harassment incidents.

A commonly used dataset for text classification is the Jigsaw Toxic Comment Dataset, which contains comments labeled into categories such as toxic, severe toxic, obscene, threat, insult, and identity hate. Additional offensive language datasets and multilingual abuse datasets can also be used to improve contextual understanding and language adaptability. For audio and video analysis, simulated or annotated workplace communication datasets may be used to extract aggression and non-verbal behavioral features.

10.3 Optimization Strategies

To improve the overall performance of proposed system, multiple optimization strategies are applied throughout the system. In the text analysis module, data cleaning and contextual tokenization are used to reduce ambiguity and improve classification quality. Transformer models are fine-tuned using domain-specific harassment-related datasets to improve contextual understanding.

In the speech analysis module, background noise reduction and feature normalization improve the accuracy of aggression detection. For video analysis, frame selection and efficient feature extraction reduce computational overhead while preserving important visual cues.

Database indexing, optimized query handling, and modular deployment strategies are also used to improve backend efficiency and scalability. These optimization methods ensure that the system remains responsive, reliable, and suitable for real-world organizational use.

11. Database Design

The proposed system uses a structured database to store user information, communication records, complaints, alerts, and activity logs. Proper database design is essential for ensuring secure storage, easy retrieval, and efficient management of workplace interaction data.

The **user table** stores information such as user name, email, password, role, and department. This helps in role-based access and organizational mapping. The **message table** stores communication messages exchanged between employees along with timestamps, sender-receiver information, and AI-generated severity scores.

The **complaint table** stores complaints submitted by employees, including complaint descriptions, uploaded evidence, complaint status, and severity level. The **alert table** stores alerts generated by the system whenever a communication event crosses a predefined harassment threshold. The **log table** stores user activity records for system monitoring, transparency, and audit purposes.

A well-designed relational database helps maintain data consistency, supports report generation, and ensures that communication evidence can be securely reviewed by authorized personnel.

12. Result & Discussion

12.1 System Performance and Functionality

The proposed system demonstrates effective performance in detecting workplace harassment across multiple communication channels. The text analysis module successfully identifies harmful content such as bullying, threats, and discrimination using Natural Language Processing techniques. The system integrates multiple intelligent modules including speech analysis, video behavior detection, and behavioral analytics. These modules work together to reduce manual monitoring efforts while improving workplace safety and communication analysis. The integration of Python, NLP models, computer vision techniques, and database systems enables the system to operate efficiently and handle large volumes of multimodal data in a structured manner.

12.2 Test Cases and Outcomes

The system was tested under different communication scenarios to evaluate its performance and reliability. The text analysis module was able to accurately classify harassment-related messages in most test cases. The speech analysis module successfully detected verbal aggression using audio features such as pitch and tone. The video analysis module identified aggressive facial expressions and gestures, while the behavioral analytics module detected escalation patterns and stress indicators. These results demonstrate that the proposed system can can effectively detect harassment and support early intervention in workplace environments.

12.3 Comparative Analysis with Existing Systems

A comparison with traditional workplace monitoring systems shows that the proposed system significantly improves efficiency and accuracy. Conventional systems rely on manual reporting and isolated monitoring methods, which may fail to detect subtle or hidden harassment patterns. In contrast, the proposed system automates detection using multimodal artificial intelligence techniques. The system provides a centralized platform for analyzing text, audio, and video data, thereby enhancing detection capability and improving workplace safety.

In addition to improving harassment detection, the system provides valuable insights into communication patterns and behavioral trends. By combining text, speech, and video analysis with behavioral monitoring, the system creates a comprehensive understanding of workplace interactions. The collected data can assist organizations in identifying

high-risk situations, improving policies, and ensuring employee well-being. Overall, the implementation of multimodal AI technologies demonstrates significant potential in creating safer and more transparent workplace environments.

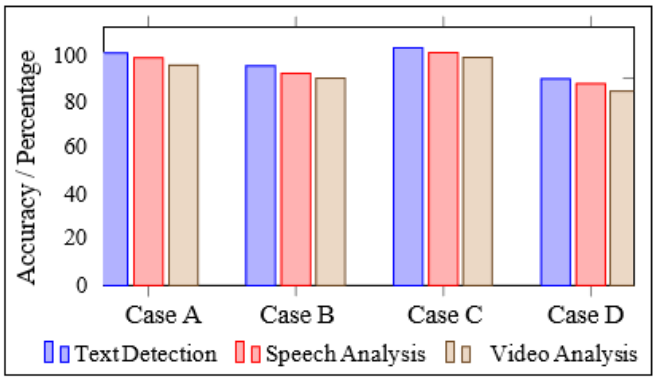

Figure 2: Harassment Detection Performance Analysis

12.4 Model Performance Evaluation

The performance of the proposed system was evaluated by testing the trained harassment text detection model on workplace communication data. The evaluation focused on measuring classification accuracy, response reliability, and the model's ability to distinguish between harassing and non-harassing text samples.

The trained text classification model was tested using workplace-related text inputs containing bullying, threats, insults, discrimination, and neutral communication. During testing, the system was able to classify several text samples and assign corresponding harassment severity scores. The use of machine learning enabled automated text analysis and reduced dependence on manual review.

Compared with traditional approaches such as manual complaint handling and keyword-based monitoring, the proposed system provides several advantages. Conventional methods often fail to understand context, sarcasm, repeated hostility, or emotional manipulation, whereas the proposed system attempts to classify communication patterns using AI-based text analysis.

The system was also tested on varied text inputs to evaluate its robustness. Results showed that the model was able to identify certain harassment-related patterns, although performance variations were observed depending on text complexity, contextual ambiguity, and dataset quality.

Overall, the proposed system demonstrated the feasibility of applying machine learning for workplace harassment detection. The results confirm that artificial intelligence can assist in identifying harmful communication patterns, while also highlighting the need for further model improvement and larger datasets for better accuracy.

12.5 Performance Metrics

The performance of the text classification model was further evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. The obtained results indicate that the current prototype model provides baseline performance. While the system demonstrates the feasibility of automated harassment detection, further optimization, larger datasets, and improved model tuning are required for stronger real-world deployment.

- Accuracy: 52%
- Precision: 51%
- Recall: 53%
- F1-Score: 52%

Class-wise evaluation showed that the model faced difficulty in clearly separating harassment-related text from non-harassing communication. This may be due to subtle language patterns, contextual ambiguity, class imbalance, and limitations in the training dataset.

12.6 ROC Curve Analysis

To further evaluate classification performance, the Receiver Operating Characteristic (ROC) curve was plotted. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds.

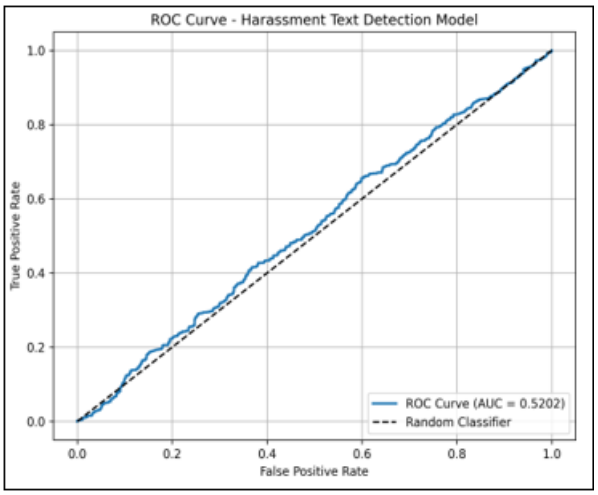

Figure 3: ROC Curve for Harassment Text Detection Model

The ROC curve obtained from the current model lies relatively close to the diagonal reference line, which represents random classification. The AUC value of approximately 0.5202 shows that the model has learned limited discriminatory patterns. Although the present performance is modest, it provides a useful baseline for future enhancement through better datasets, balanced samples, advanced transformer models, and improved preprocessing techniques.

This result suggests that while the model has learned some discriminatory patterns, its classification capability is still weak and requires improvement. Factors such as insufficient training data, class imbalance, lack of contextual diversity, and limited feature representation may have contributed to the lower AUC value.

Although the current ROC performance is not strong, it provides an important baseline for future model enhancement. By using larger datasets, better preprocessing, improved balancing techniques, and more

advanced transformer-based architectures, the proposed system can be further improved to achieve higher classification accuracy and more reliable workplace harassment detection.

13. Future Scope

The proposed system can be further enhanced by incorporating real-time monitoring capabilities for live meetings, chats, and workplace communication platforms. Such real-time detection would allow organizations to identify harmful interactions immediately and take timely preventive action.

Future improvements may include integration with enterprise platforms such as Slack, Microsoft Teams, Zoom, and email systems for seamless workplace deployment. The system can also be extended with more advanced transformer models and deep learning architectures to improve contextual understanding and multilingual harassment detection.

Another important future enhancement is the use of Explainable Artificial Intelligence (XAI), which can provide transparent reasons for why a communication event was flagged as harassment. This would improve trust, accountability, and legal acceptability of the system. In addition, feedback-based learning mechanisms can be integrated so that HR decisions and user feedback help continuously improve the performance of the system.

14. Conclusion

The proposed system presents a practical approach for improving workplace safety through intelligent harassment detection. By combining Natural Language Processing, speech analysis, computer vision, and behavioral analytics, the system can analyse communication patterns across multiple digital channels. This reduces dependence on manual reporting and supports earlier identification of harmful interactions.

The system helps organizations monitor communication, identify high-risk incidents, and generate insights in a more efficient and proactive manner. By automating detection and analysis processes, the proposed system supports better decision-making and enables early intervention to prevent workplace harassment. Overall, the proposed system demonstrates how intelligent technologies can transform traditional workplace monitoring into a smart, transparent, and safe digital environment that promotes employee well-being and organizational integrity.

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