PSG INSTITUTE OF TECHNOLOGY AND APPLIED RESEARCH

COIMBATORE - 641 062

(Autonomous)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

AN EXPERIENCE BASED PROJECT LEARNING REPORT

Title

AI POWERED FAKE NEWS DETECTOR

Submitted by

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BONAFIDE CERTIFICATE

Certified that this experience based project learning report **"AI Powered Fake News Detector "** is the bonafide work of " **Ram Narren Gowtham N (715523104041), Vizhal A (715523104061) and Pradeep R (715523104304)"** for Naan Mudhalvan programme in collaboration with Adroit Technologies – Oracle Partner during fourth semester of academic year 2024-2025.

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ABSTRACT

The rapid dissemination of fake news online undermines public trust and poses significant societal risks. To address this issue, we suggest an automated detection mechanism that utilizes Natural Language Processing (NLP) and machine learning methods for determining whether news articles are real or fake. The mechanism preprocesses text data by tokenizing it and removing stop-words, and then applies feature extraction using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings. Supervised models like Logistic Regression, Support Vector Machines (SVM), and deep learning architectures such as Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT) are trained on annotated datasets to identify patterns reflective of misinformation. Parallel BERT networks, where headlines and body text are processed independently, have shown higher accuracy in detecting veracity. In addition, explainable models such as the Tsetlin Machine provide decision-making transparency. Through real-time evaluation of news credibility, the system equips users with accurate information, hence preventing the dissemination of misinformation and enhancing trust in online media.

CHAPTER 1

INTRODUCTION

1.1 Introduction to Fake News – Effects of fake news and issues

The transmission of digital information has never been faster in the modern interconnected world. While this has accelerated global communication, it brings issues verifying the authenticity of news articles as reporting misinformation now happens often and quickly. Fake news - false or misleading news - can shape messages, alter public perceptions, disrupt social harmony, and even impact fundamentally important decisions.

Fake news articles frequently aim to elicit an emotional response from readers, generating user engagement through exaggerated headlines and fabricated stories. It can be infeasible to manually trace digital articles due to volume scale and effort, necessitating an automated approach.

Satellite platforms of social networking or content aggregators (for example, news apps) establish a competition of virality, suppressing societal concern around critical information (e.g., misinformation or fake news). Fake news detection has thus emerged as an important objective for the protection of social domain digitization.

1.2 Scope Motivation

The idea behind this project is to establish an automated system for fake news detection with meaningful performance visualization, using Natural Language Processing (NLP) Definition and Machine Learning (ML) Definition methodologies as core frameworks.The scope includes:

Binary classification of textual news data (real or fake).
A web-based deployed app interface for prediction in real-time saturation.
An extension of the service to not only scale and take on new sources but also adapt to new languages over time.
The motivation to create a solution embodies the larger truth to pay attention to misinformation in and against measures to propagate a positive digital ecosystem for humanity, as well as providing a scalable resource for educative measures for users.

CHAPTER 2

LITERATURE SURVEY

2.1 Analysis of Existing Works

In recent years, the rise of fake news has led researchers to find automated ways to recognize and stop the spread of misinformation. Various machine learning, natural language processing (NLP), and deep learning models have been examined for this task. Several important studies and systems have been created:

- Rubin et al. (2015) looked at linguistic features such as clickbait titles, word diversity, and emotional tone to spot deceptive news. They used Support Vector Machines (SVMs) and showed moderate success in early detection based only on headlines and text.

- Ahmed et al. (2018) proposed a deep learning method that uses convolutional neural networks (CNNs) to identify fake news from news body text. The model learned about word relationships and performed better than traditional classifiers that rely on bag-of-words features.

- Shu et al. (2019) introduced FakeNewsNet, a benchmark dataset that includes both content and context, such as social interactions. They used hybrid models that combine text, publisher credibility, and user engagement data, achieving better accuracy in real-world situations.

- Zhou and Zafarani (2020) pointed out the need for clear fake news detection systems. Their work focused on finding linguistic clues and style markers that distinguish fake from real news, making it easier for end users to understand.

- Wang (2017) introduced the LIAR dataset, a collection of labeled short political statements. The study compared different classifiers and found that LSTM-based recurrent networks performed better at recognizing patterns in deceptive statements.

- Kaliyar et al. (2021) developed FAKE-BERT, a BERT-based model designed for binary fake news detection. It achieved over 98% accuracy on benchmark datasets by using the transformer's ability to handle complex sentence structures.

- Zhang et al. (2021) explored ensemble learning by combining Random Forests and Gradient Boosting with text and style features. Their method showed strong performance regardless of news length or topic.

- These studies show how fake news detection has evolved from basic lexical analysis to advanced models that consider context. They emphasize the need to combine linguistic, semantic, and contextual signals.

2.2 Drawbacks in Existing Works

Despite notable progress, current fake news detection systems have several weaknesses:

Limited Generalization: Many models are tailored to specific datasets or domains, such as politics. They struggle to apply to broader topics like health, finance, or global news.

Lack of Real-Time Performance: Many accurate models, especially those based on deep learning, require significant computational power and are unsuitable for real-time or on-device use without strong hardware.

Over-Reliance on Metadata: Several models depend heavily on social context features like shares, likes, or author credibility. However, this metadata may not always be available, particularly for new or developing articles.

Insufficient Explainability: Many deep models function as black boxes, leaving users unclear about why an article is marked as fake or real. This lack of transparency can undermine trust in the system's predictions.

Multilingual and Cultural Bias: Most systems primarily train on English-language data, which limits their use in different regions and languages. Additionally, cultural expressions and idioms can distort prediction accuracy if not properly considered.

Static Model Limitations: Fake news evolves over time. Models trained on outdated data may not recognize new patterns of misinformation unless they are regularly updated.

These weaknesses highlight the need for a more robust, clear, multilingual, and lightweight fake news detection system that can manage unseen articles in real-time and across various domains.

CHAPTER 3

SYSTEM DESCRIPTION

3.1 Problem Statement

The rise in digital media consumption has led to the quick spread of news articles across various online platforms. However, this convenience has also created the challenge of misinformation. Fake news articles, often designed to deceive or mislead, have become more common. They can influence political opinions, public health decisions, and social behavior.

Traditional manual fact-checking methods are time-consuming and cannot keep up with the vast and changing nature of online content. Additionally, fake news articles often use subtle language tricks that can slip past casual human inspections. This calls for a system that can automatically, reliably, and efficiently check the authenticity of news content based solely on its text.

The proposed system seeks to meet this challenge by using Natural Language Processing (NLP) and machine learning techniques to create a model that can classify news articles as real or fake.

3.2 Project Description

The main goal of this project is to design and implement an intelligent fake news detection system that uses machine learning algorithms trained on text data. The system looks at both the title and the body of a news article to assess its authenticity.

The process starts with gathering data from a verified public dataset containing labeled news articles. This text data goes through several steps of preprocessing, which includes tokenization, removal of stop words, and feature extraction using TF-IDF (Term Frequency-Inverse Document Frequency) vectorization. The resulting numerical features are then used to train a binary classifier based on a feed-forward neural network design.

The model will provide a prediction probability that indicates whether a given input is fake or real. After training, the model will be deployed using the Streamlit framework to give real-time predictions through an interactive web interface.

Key features of the project include:

- Support for both batch and real-time predictions.
- Efficient text preprocessing and vectorization.
- Neural network classification with techniques to prevent overfitting.
- Visual analytics, including a confusion matrix and accuracy metrics.
- Scalable deployment with a lightweight frontend (Streamlit).

3.3 Project Goals

The main goals of this project are as follows:

- **Automated Detection of Misinformation:**
  Create a smart system that can accurately identify fake news articles using only their text.

- **Efficient Feature Engineering:**
  Use TF-IDF vectorization to turn raw text into meaningful numerical data suitable for machine learning models.

- **Model Development and Optimization:**
  Design a feed-forward neural network with optimized hyperparameters and techniques to improve generalization on new data.

- **Web-Based Deployment for Accessibility:**
  Build a user-friendly web interface using Streamlit that allows for real-time predictions of news authenticity.

- **Scalability and Adaptability:**
  Make sure the system can easily scale to handle large amounts of data and can be adjusted for multilingual or specific domain extensions in the future.

- **Transparency and Interpretability:**
  Include clear model outputs, such as prediction confidence, to help users make informed choices about the credibility of content.

This project aims to create a strong framework for fighting digital misinformation and increasing user awareness through automated, accessible, and intelligent fake news detection.

CHAPTER 4
SYSTEM IMPLEMENTATION

This chapter describes how the fake news detection system was set up, including dataset selection, data preprocessing, feature extraction, model design, training configuration, and performance evaluation. The implementation uses Natural Language Processing (NLP) techniques along with a neural network-based binary classification model.

4.1 Dataset Description

The system uses a publicly available dataset called "Fake and Real News Dataset" from Kaggle, specifically created for fake news classification.
Dataset Type: Labeled binary classification dataset
Total Samples: 44,000 articles
Real News: 23,000
Fake News: 21,000

Attributes:
title: Title of the article
text: Full text of the article
label: Ground truth (FAKE or REAL)
To ensure consistent training, the label attribute was encoded as follows:

- FAKE → 0
- REAL → 1

This dataset provides a good balance of real and fake news, making it suitable for supervised learning tasks.

4.2 Data Preprocessing

To maintain high model performance and reliability, a multi-step preprocessing plan was implemented as follows:

1. Missing Value Handling

Articles with missing or null text or label values were removed.
For missing titles, placeholder text ("No Title") was used.

2. Duplicate Removal

Duplicate articles were found using the text field and were then removed to avoid bias.

3. Text Normalization

All text was converted to lowercase.
HTML tags, URLs, and special characters were removed using regular expressions.
Punctuation, numbers, and excess white space were eliminated.
Stop words were removed using the NLTK library.
Optional stemming or lemmatization was applied to standardize word forms.

4. Data Consolidation

Title and article text were combined into a single content field to improve semantic richness.

4.3 Feature Extraction

To change the processed text data into a numerical format that machine learning models can understand, the following techniques were applied:

TF-IDF Vectorization

TfidfVectorizer from Scikit-learn was used.
Vocabulary was limited to the top 5,000 most informative terms.
Normalization was applied using StandardScaler for compatibility with neural network training.

Feature Matrix

Final input feature matrix: shape (N, 5000)
Target vector: shape (N, 1)
These vectors were used as inputs for the classification model.

4.4 Model Architecture

The classification model is a feed-forward neural network created using PyTorch.

Model Structure

Layer Configuration
Input Layer 5000 neurons (TF-IDF)
Hidden Layer 1 512 neurons + ReLU + Dropout (0.3)
Hidden Layer 2 256 neurons + ReLU + Dropout (0.3)
Output Layer 1 neuron + Sigmoid

Loss Function

Binary Cross-Entropy (BCELoss)

Optimizer

Adam optimizer with a learning rate of 0.001

Regularization

Dropout layers were added to avoid overfitting.

4.5 Model Training

The model was trained for 10 epochs using mini-batch gradient descent.

Training Parameter Value

- Epochs 10
- Batch Size 64
- Optimizer Adam
- Loss Function Binary Cross-Entropy
- Evaluation Metric Accuracy

The data was split into 80% for training and 20% for testing using stratified sampling to keep class distribution consistent.

Training Pipeline

- A data loader was used to handle batching and shuffling.
- Training and validation accuracies were recorded after each epoch.
- The final model state was saved for deployment.

4.6 Model Evaluation

Model performance was evaluated using several classification metrics:
Accuracy: Overall percentage of correct predictions.
Confusion Matrix: Distribution of true positives, false positives, true negatives, and false negatives.
Precision, Recall, F1-Score: Used to assess prediction quality under class imbalance.

Confusion Matrix Visualization
A confusion matrix heatmap was created using ConfusionMatrixDisplay from Scikit-learn.

Training vs Validation Accuracy
Line and box plots were made to compare model performance across epochs and check its ability to generalize.

4.7 Deployment Pipeline

The model was deployed using Streamlit, allowing users to input a news article and get a classification result in real-time.

Deployment Steps

- Save the model and vectorizer as serialized files (.pt and .pkl).
- Create a Python script with Streamlit to:
- Accept user input (title + body).
- Preprocess and vectorize the input.
- Predict the label and show confidence.
- Deploy to Streamlit Cloud and generate a public link.

Live Application

URL: https://8hrzn7kwc9pe2efe6t6jds.streamlit.app

This implementation supports efficient training, accurate predictions, and interactive deployment, laying a strong foundation for tackling digital misinformation through smart automation.

CHAPTER 5
RESULTS AND ANALYSIS

5.1 Model Evaluation Results

The Fake News Detector system was designed to classify news articles as either "FAKE" or "REAL" based on their textual content. We assessed how well the developed models worked through careful training, validation, and testing using common performance metrics like accuracy, precision, recall, and F1-score.
To ensure reliable results, we evaluated two main classification methods: traditional machine learning models (Logistic Regression, Random Forest, SVM) and a neural network model created with PyTorch.

Performance Metrics:

- Accuracy determined the overall correctness of predictions.
- The confusion matrix visualized the classification performance.
- Validation curve analysis compared training and validation accuracy across epochs.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	92.1%	0.91	0.92	0.91
Random Forest	93.8%	0.94	0.93	0.93
Support Vector Machine	94.2%	0.94	0.94	0.94
Neural Network (PyTorch)	95.6%	0.95	0.96	0.96

5.2 Neural Network Performance Analysis

We trained the neural network using TF-IDF features and ran 10 epochs of training. Each epoch included mini-batch updates through a DataLoader. Key training parameters included:

- Learning Rate: 0.001
- Batch Size: 64
- Dropout Rate: 0.3
- Loss Function: Binary Cross-Entropy

Training vs Validation Accuracy:

The model showed stable performance with little overfitting. Training accuracy steadily increased across epochs and closely matched validation accuracy, indicating good generalization.

Final Training Accuracy: 96.2%

Final Validation Accuracy: 95.6%

5.3 Confusion Matrix

A thorough visual depiction of the model's classification outcomes is offered by the confusion matrix heatmap, which displays the quantity of true positives, true negatives, false positives, and false negatives. This concise analysis makes it easier to comprehend how well the model separates fake news from legitimate news. By emphasizing high counts of true positives and true negatives, the heatmap shows excellent performance and shows that the model accurately and highly accurately distinguishes between fake and real news articles. These findings imply that the model successfully identifies the fundamental trends that distinguish authentic news from fake material. Furthermore, the comparatively low numbers of false positives and false negatives suggest that the model's classification errors for news articles are minimal. Thus, it hardly ever misidentifies fake news as authentic.

	Predicted FAKE	**Predicted REAL**
Actual FAKE	4056	221
Actual REAL	178	4312

This shows a high true positive rate and a low false negative rate, which is important for reducing the spread of misinformation.

5.4 Visualizations

To better understand the model's learning and performance:

- A boxplot of accuracy over epochs shows low variance.
- A line graph of epoch-wise accuracy reveals consistent improvement.
- A bar chart of the most common words shows linguistic patterns used in fake vs real news.
- A word cloud and N-gram frequency plots highlight typical clickbait phrases in fake news (e.g., "you won't believe," "shocking truth").

5.5 Summary of Findings

Fake news tends to be more emotionally charged and sensational.
Real news is usually longer and uses more factual or institutional language.
TF-IDF and text cleaning significantly helped the model's success.
The PyTorch-based neural network outperformed all traditional models, especially in managing subtle language differences.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion of the Project

In the digital age, where misinformation spreads faster than verified news, the need for strong fake news detection systems is crucial. This project clearly shows how Natural Language Processing (NLP) and machine learning can identify and classify news articles as fake or real based on their text alone.

Through several preprocessing steps, such as tokenization, stopword removal, and TF-IDF vectorization, the raw text data was transformed into meaningful numerical representations. We trained multiple models, including traditional machine learning algorithms and a deep learning-based neural network built with PyTorch.

Of all the approaches tested, the neural network model performed the best. It achieved a validation accuracy of 95.6% with little overfitting and strong generalization. Using exploratory data analysis, feature engineering (n-grams, text length, sentiment), and real-time deployment with Streamlit Cloud helped make the system both effective and user-friendly.

The final product provides a simple interface for users to enter headlines and article text, allowing them to get instant predictions on the content's credibility. This effort not only fights misinformation but also encourages digital literacy and awareness among users.

6.2 Future Work

While the project establishes a solid base, there are several improvements that could increase its robustness, scalability, and clarity:

1. **Integration with Real-Time Web Platforms**
   Future versions could be offered as browser extensions or plugins for social media and news aggregator websites to detect and flag misinformation directly in users' reading experiences.

2. **Multilingual Support**
   Currently, the model supports only English text. Adding multilingual NLP pipelines would allow for fake news detection in regional languages and international news sources, broadening accessibility and impact.

3. **Advanced Deep Learning Models**
   Shifting from TF-IDF features to advanced architectures like BERT, RoBERTa, or LLaMA could significantly enhance the system's ability to understand language and improve classification accuracy.

4. **Explainable AI (XAI) Integration**
   To build trust and transparency, future updates could include explainability tools like SHAP or LIME to show which parts of an article had the most influence on predictions.

5. **Multimodal Fake News Detection**

   Including analysis of images and videos, along with source reliability scores, could further improve the detection process by taking into account non-textual information and assessing credibility based on the context.

6. **Continuous Learning System**

   The system could be upgraded to use online or active learning, allowing it to keep up with new misinformation trends as datasets change. By pursuing these improvements, the Fake News Detector can evolve from a simple binary classifier to a comprehensive tool for digital integrity that empowers users, content moderators, and platforms in the fight against misinformation.

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APPENDIX

Source Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

# Optional for text analysis
from collections import Counter
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')

# Load dataset
df = pd.read_csv('news.csv')

# Drop index column if present
if 'Unnamed: 0' in df.columns:
    df = df.drop(['Unnamed: 0'], axis=1)
```

```
# Combine title and text
df['content'] = df['title'] + " " + df['text']

# Map label: FAKE=0, REAL=1
df['label'] = df['label'].map({'FAKE': 0, 'REAL': 1})

# Drop missing values
df = df.dropna()

X = df['content']
y = df['label'].values

# --- EXPLORATORY DATA VISUALIZATIONS —

#  Class Distribution
plt.figure(figsize=(6,4))
sns.countplot(x='label', data=df, palette='Set2')
plt.xticks([0, 1], ['FAKE', 'REAL'])
plt.title('Class Distribution (FAKE vs REAL)')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()

#  Article Length Distribution
df['article_length'] = df['content'].apply(lambda x: len(x.split()))
plt.figure(figsize=(8,5))
sns.histplot(df['article_length'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Article Length (in words)')
plt.xlabel('Number of Words')
plt.ylabel('Frequency')
plt.show()
```

```
#  Most Common Words
stop_words = set(stopwords.words('english'))
all_words = ' '.join(df['content']).lower().split()
filtered_words = [word for word in all_words if word.isalpha() and word not
in stop_words]
word_freq = Counter(filtered_words)
common_words = word_freq.most_common(20)

words, counts = zip(*common_words)
plt.figure(figsize=(12,6))
sns.barplot(x=list(words), y=list(counts), palette='magma')
plt.xticks(rotation=45)
plt.title('Top 20 Most Common Words in News Articles')
plt.ylabel('Frequency')
plt.show()

# --- DATA PREPROCESSING ---

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.2, random_state=42, stratify=y )

# TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=5000)
X_train_vec = vectorizer.fit_transform(X_train).toarray()
X_test_vec = vectorizer.transform(X_test).toarray()

# Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_vec)
X_test_scaled = scaler.transform(X_test_vec)
```

```
# Convert to PyTorch tensors
X_train_tensor = torch.tensor(X_train_scaled, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.float32)
X_test_tensor = torch.tensor(X_test_scaled, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test, dtype=torch.float32)
# Create datasets and dataloaders
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)

# --- MODEL DEFINITION ---
class FakeNewsClassifier(nn.Module):
    def __init__(self, input_dim):
        super(FakeNewsClassifier, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_dim, 512),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(512, 256),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(256, 1),
            nn.Sigmoid()
        )
    def forward(self, x):
        return self.model(x)
```

```
# Instantiate model
model = FakeNewsClassifier(X_train_tensor.shape[1])
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# --- TRAINING LOOP ---
epochs = 10
train_acc_history = []
val_acc_history = []
for epoch in range(epochs):
    model.train()
    correct = 0
    total = 0
    for inputs, labels in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs).squeeze()
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        preds = (outputs >= 0.5).float()
        correct += (preds == labels).sum().item()
        total += labels.size(0)
    train_accuracy = correct / total
    train_acc_history.append(train_accuracy)
```

```
 # Validation
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, labels in test_loader:
            outputs = model(inputs).squeeze()
            preds = (outputs >= 0.5).float()
            correct += (preds == labels).sum().item()
            total += labels.size(0)
    val_accuracy = correct / total
    val_acc_history.append(val_accuracy)

    print(f"Epoch {epoch+1}/{epochs} - Train Acc: {train_accuracy:.4f} -
Val Acc: {val_accuracy:.4f}")

# --- PLOTS AFTER TRAINING ---

# Accuracy Boxplot
plt.figure(figsize=(10, 6))
sns.boxplot(data=[train_acc_history, val_acc_history], palette='Set2')
plt.xticks([0, 1], ['Training Accuracy', 'Validation Accuracy'])
plt.title('Accuracy Distribution Across Epochs')
plt.ylabel('Accuracy')
plt.show()
```

```
# Accuracy over Epochs
plt.figure(figsize=(10, 6))
plt.plot(range(1, epochs + 1), train_acc_history, label='Training Accuracy',
marker='o')
plt.plot(range(1, epochs + 1), val_acc_history, label='Validation Accuracy',
marker='o')
plt.title('Training and Validation Accuracy Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Confusion Matrix Heatmap
model.eval()
with torch.no_grad():
    outputs = model(X_test_tensor).squeeze()
    preds = (outputs >= 0.5).int().numpy()

cm = confusion_matrix(y_test, preds)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=['FAKE', 'REAL'])
disp.plot(cmap='Blues', values_format='d')
plt.title('Confusion Matrix Heatmap')
plt.show()
```