International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

Live Fake News Detection using ML

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Abstract — Fake news aims to trick people on purpose. Because social media grows so fast, lies spread quickly too. It's key to check if a story is true or not. This study uses machine learning to spot fakes versus real content. Looking closely at words, pictures, clips, plus pulling out useful details helps improve results. In this case, we checked several machine learning tools for spotting false stories. After testing them out, it turned out Random Forest along with Linear Regression did better than the rest - hitting a 90.1% success rate.

Keywords – Fake News, feature Extraction, Machine Learning, Real News, Social Media.

I. INTRODUCTION

The term "Fake News" means spreading info that's been twisted or made up - stuff you can prove wrong by checking facts. When people create fake news on purpose, they trick readers into believing lies. As more folks use online platforms to share thoughts and views, it gets easier for false stories to pop up. This makes spotting and removing fake news super tough because real and fake often look almost exactly alike. To tell them apart, tools like TF-IDF and Cosine check how similar the words really are similarity threshold, CNN layers, frame sampling rate, hashing method. News might get twisted to pull focus away from real stories - just for clicks. We use machine learning tools to check content and spot fake patterns. Uses pop up on social platforms, news sites, reporters, even health alerts. Sharing clear, exact info matters when choices are on the line. Finding fake news helps keep trust in companies, media, and groups. Checking facts by hand tends to be slow, tiring, often biased, plus it doesn't scale well. As tech and smart software have grown, automated tools now fight lies more reliably. In this study, a tool that detects false info was built using several machine learning and language processing tricks. The setup uses logistic regression along with TF-IDF vectorizing techniques.The performance of every machine learning and natural language model gets judged

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by accuracy, precision, or recall. During the COVID-19 outbreak, fake stories moved faster than real ones - causing fear, chaos, spreading across countries. Computers using smart methods offer a solid fix for issues like these. These systems spot patterns, word choices, situations instead of just facts to tell truth from lies.

II. LITERATURE REVIEW

In recent times, spotting fake news got more attention - thanks to how fast false info spreads online. Earlier work mostly used basic machine learning tricks - think Logistic Regression or Naive Bayes - or even Random Forests. These tools ran on manually picked traits - one example's n-grams - then things like word types - mood signals - and how easy a piece is to read. Beyond just words, newer attempts explored mixed approaches; they tied article text to photos - social activity - even checked how stories travel across networks. A few standard sets - LIAR for instance - FakeNewsNet - or collections around pandemic lies - help test these systems side by side.

In spite of progress, problems remain. Still, models often fall short when hit with fresh scenarios or new topics. Because real-world data carries bias, results might not hold up everywhere. Yet people who use these tools - and those checking facts - need clear reasons behind decisions. So work pushes forward, focusing on broader adaptability, blending multiple methods, while building AI that shows its thinking for better fake news spotting. Even with big steps forward, hurdles pop up now and then. For instance, what works on one set crumbles in unknown areas or during fast-moving stories. Besides, label accuracy wobbles - verifying claims takes time, leading to messy annotations. On top of that, sneaky tactics like slight word tweaks trip current systems easily. Worst part? Most smart algorithms hide their logic, leaving regular users skeptical unless they see understandable justifications.

Since it's tough to get large verified datasets, researchers look into semi-supervised methods - alongside unsupervised clustering - to spot false info. These techniques work with raw, untagged data or reveal underlying trends, making them well-suited for real-life cases where labeled examples are scarce.

In a study, experts built a tool to sort web news into real or fake. Yet they checked it carefully afterward. Their approach included several main stages: still, each step was handled one at a time

a) Using the Data – The team worked with a dataset of news articles that's free to access, which included labels, meaning each piece was sorted into categories

real or forged reports - the data mostly focused on written stuff, like articles along with titles

b) Cleaning Text Steps – First, split words into pieces; then tidy them up by simplifying forms while tossing out useless ones prior to teaching algorithms.

c) Algorithms – A bunch of different ML methods got tested - like Naive Bayes, SVM - but also Decision Tree models.

d). Evaluation & Outcomes – We checked how well the models worked using accuracy along with other measures. The LSTM model hit about 95% correct answers when telling real from fake news stories.

In a different study, researchers looked at how major Indian TV news helps spread misinformation via social platforms. While these outlets sometimes give space to untrue claims, they also use online networks in ways that push deceptive stories further. Instead of just reporting facts, their actions often speed up the rise of false

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narratives. With inaccurate reports gaining ground fast, experts worry about fixing this issue - especially since popular media tends to overshadow fairer, more balanced sources today.

III. METHODOLOGY

The ways we've tried to catch fake news are shown in Figure1(a). This technique starts by taking info - like articles, posts, or links - from the user. Once received, it sends that data to the back end for handling. Next up, key traits get pulled out automatically. The API client works as a middle layer linking front and back systems. Sends a request from frontend to backend - then waits for reply. After that, the backend pulls info through an API client, handles it, before triggering the MachineLearning engine for guesses. Then comes news analyzer which checks the given text, runs tests to spot if it's fake or genuine. Lastly, deployment keeps all pieces moving in order, without chaos.

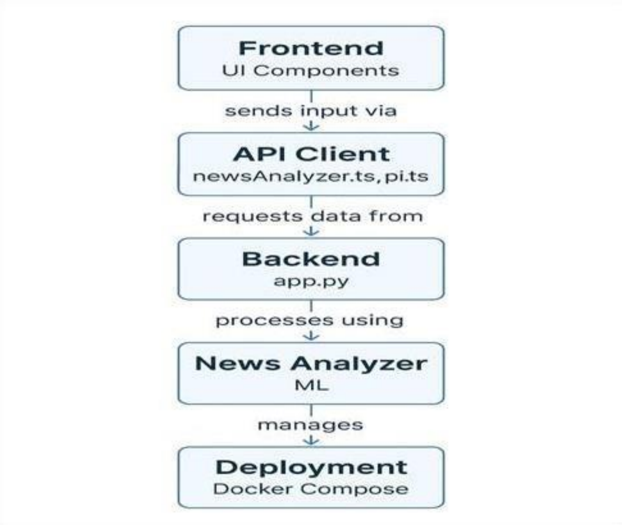

Fig 1.Architecture

The setup described has five main pieces. First up, the 'Frontend,' where people enter their info instead. It gives visual stages so folks can add news material or data meant for checking.

After this, the info moves through the API client. This tool links the front end with the back end. Instead of just sending raw details, it asks the server nicely. Using set formats helps keep things running without hiccups.

The backend runs on main.py - handling incoming requests, then passing data along. Built using Python since it manages the system's key functions, while also directing tasks by routing inputs to machine learning models.

News Analyzer's a machine learning tool that handles news stories. It takes in articles or data, then runs tasks such as sorting them or checking emotional tone. Once it creates results, they're sent to the back end so the front end can receive them.

IV. EXPERIMENTAL ANALYSIS

A. Dataset with Algorithms: a handful of methods - like LR, TF-IDF setup plus tweaks - all aimed at catching fake news

Each update was taught with part of the data, then tested on new samples to check performance. Performance checks looked at accuracy, precision, recall, along with balanced scores. To find out how well it catches fake news, several tests ran - each using a different algorithm type. The big question? Which model tells real from fake articles best using just words. Stories came from trusted online sources tagged either "real" or "fake." Before training, steps like cleaning text, removing common filler words, breaking text down, plus turning it into numbers via TF-IDF or Count Vectorizer were done. These tweaks helped shift raw text into digits that machines can work with.

Textual spotting of false info often uses machine learning along with natural language processing to craft convincing content. Instead of just linking ideas, these systems rely on smart models that build smooth, fitting text based on a given prompt

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or theme. Trained using massive data collections, such tools learn how words flow together - so they can write stuff nearly like people do. When fed a title or idea, they whip up full stories or articles that seem real at first glance. Thanks to deep pattern recognition, they catch subtle tone shifts, keep logic steady, and copy specific writers' voices or types of storytelling.

Because of advances in AI and machine learning, spotting fake info has become a powerful tech tool today. Yet the growing number of deepfake problems sparks serious ethical worries. These fakes involve changing digital material on purpose - creating false images of folks or happenings - which can trick people, push lies, and damage communities. Looking at pictures and videos plays a key role in catching deepfakes made by altering visual and sound elements. To detect these fakes, experts use different techniques to study media files, searching for odd details or glitches that hint at tampering. Important tools and clues used in this process include:

Inconsistency in Resolution: Deepfake visuals might show mismatched clarity, focus, or graininess. Since editing alters parts of a clip, some sections look sharper while others appear blurry - depending on how they were processed.

Looking at timing: this means checking how face changes match up across a video's timeline. When motions feel off or don't flow right, that might hint at fake content.

Metadata tells when and where a file was made, plus any changes done later. Fake news checkers look at this info to see if media is real or not. Among tested models, Logistic Regression worked best - hitting top scores across every measure without leaning too much one way. That means it's strong for sorting texts, like spotting false stories.

A. Algorithms Used:

The system mixes NLP-driven and vision-focused tools - checking if text and images look real or fake through combined analysis

1. Text :: For links or written content, it checks how close the meaning is by using word importance scoring positive similarity math when matched against real articles. When a web address pops up, it confirms legitimacy through trusted site screening.

2. Image spotting: CNN setups learn to spot important bits by studying real news pics. Instead of basic layers, this one picks ResNet-50 to dig into complex patterns. After that, a dense softmax link wraps up the sorting job.

B. Graphical Analysis: The results reveal how well fake news is spotted really depends on what kind of data goes in - also, the traits being checked change things a lot.

The model handles text data really well, hitting high accuracy levels. That said, methods like TF-IDF, BERT, or LSTM are good at picking up on language patterns found in fake news. These tools grasp tone, meaning, and wording fairly accurately. So, despite differences, they perform solidly when spotting misleading content.

Links score nearly perfect - maybe 'cause they're checked by site reputation, like known good spots or blocked lists, so real vs fake stands out clear.

Picture data (~78%) - Spotting fakes through images works okay. Tools such as CNN or borrowed models (like VGG16, ResNet) help catch tricked visuals; however, catching image lies stays tough because changes can be tiny or old pics reused.

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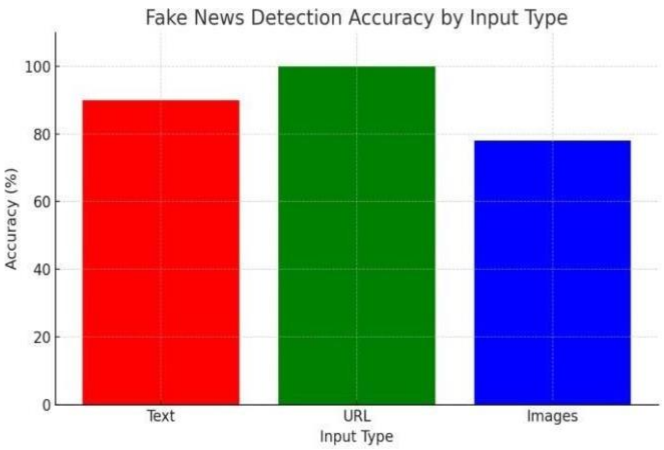

Fig 2.Bar chart represention of result

C. Problem Statement: Trouble with data - no big or varied collection of reliable images, videos, or sites yet. Needs constant refreshes when fresh approved or blocked material shows up.

D. Algorithmic Challenges:

i TF-IDF/BM25 fail with rephrased queries or when keywords aren't used.

ii CNN embeddings take a lot of computing power when used on video frames

iii Hashing techniques don't work well when images are cropped or edited with filters. These changes cause issues in real-world use

v4 Scalability: Searching through millions of docs or images using embeddings needs special vector DBs - like FAISS, Pinecone, or Milvus.

v Latency: Semantic search takes more time compared to keyword-based lookup.

ví Domain Check: Good domain lists need frequent updates yet solid checks now and then.

vii Mixed-mode blending: combining text, yet linking images along with video lookups isn't easy.

V. RESULT

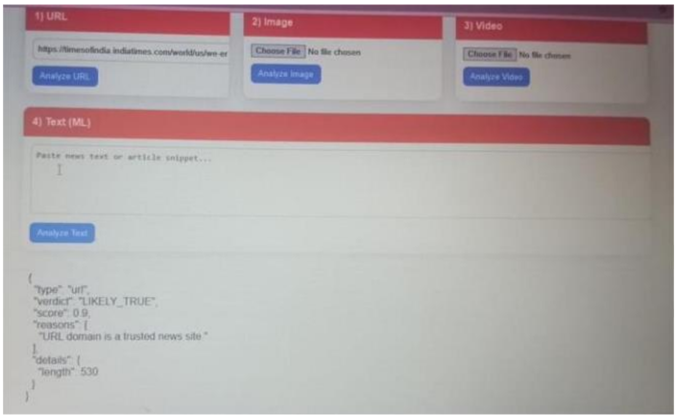

Fig.3.Url form detection

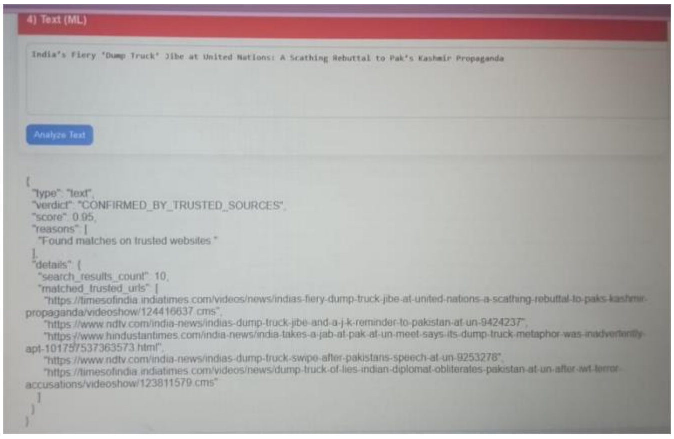

Fig.4.Text format detection

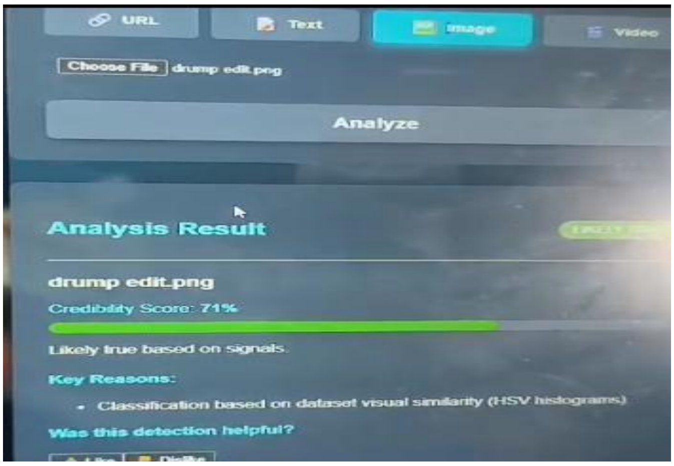

Fig. 5.Image format detection

VI. CONCLUSION

This study looked at how machine learning helps tackle the growing issue of spotting false news. Thanks to progress in multi-modal analysis,

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social network patterns can now be studied more deeply. Transfer learning has also expanded what automated tools can do in catching misleading info. On top of that, clear results and understandable models matter a lot.It's key to build forecasts that work well, are quick, yet still fair when used out in real life situations.

VII. FUTURE WORK

A. Spotting Fake Videos: Use CNNs like XceptionNet or VGG16 for checking images and videos, so fake stuff can be caught more easily.

B. Works in many languages – like Hindi, Kannada, Tamil, or Telugu – when spotting text.

C. Live News Checker for Your Browser: Build a tool that works right inside Chrome or Edge - spots fake stories the moment you load a page, no delays. It runs quietly in the background, checking sources as you scroll through sites.

D. Adding fact-check tools: Hook up Google's Fact Check tool, connect PolitiFact, use AltNews data to confirm statements.

E. Scaling up: Move from SQLite to a cloud database - like PostgreSQL or MongoDB, maybe AWS RDS - when data grows too large.

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