

# The Role of Social Media in Destination Selection & Content Authenticity Verification

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**Abstract**— In the digital age where social media is a big player in influencing masses, thinking, and action-to-be-adverse in millions of public that are being decrease for travel, tourism pressurize. Travelers tap into Instagram, YouTube, Facebook and Twitter to find new places, share experiences and access inspiration from travel influencers. For travelers looking for recommendations,[5] social media is the ultimate power to develop travel trends. Nevertheless, as is typical with content posted to social media the authenticity of the majority of the content is under scrutiny due to fake review now considered jaded and surfacing sponsored posts/influencer validation statements/ played images[4]. It erodes the confidence travellers have in these platforms to help them choose where to travel. Purpose of the Research. This study aims to investigate the role of social media in this decision making process of traveler and if influence of fake and misleading content. More specifically, it addresses how social media influencers and user generated content (blog posts, pictures) influence the perception of a destination. The research also investigates upcoming tech innovations combating the dangers of fake news, examining Artificial Intelligence (AI) and Block chain as a way to approve the authenticity of content[8]. Using the tools of primary surveys, secondary data findings and AI algorithms for detecting fake reviews; the research aimed at identifying whether or not these technologies act to antidote travel content credibility. Results of the research will be of profound importance to the future of travel marketing and compose a call to responsibility in regard with travelers as well content creators.

**Keywords**— *social media, destination selection, content authenticity, AI, Block chain, fake reviews*

## I. INTRODUCTION

Social media is a powerful medium in tourism and provides rich information about destination from the masses. Social media platforms such as Instagram and YouTube are not just a social outlet but also effective marketing channels that[8]dictate everything from how we choose our travel

destination to deciding where we are going. Travelers look to social media for visual inspiration, curation and in real time finds on destinations to visit, places to stay, what to do. Specifically influencers as they also heavily influence destination choice through both sharing their travel experiences and making recommendations. The emergence of destination marketing occupation in which destinations actively market and brand their destination has been fueled by the attention grabbing potential of destination content. However blurring the line between authentic and sponsored pieces,[2] as many influencers are putting out destinations for compensation and failing to disclose often. The result is pervasive double standards on how we travel, where fake reviews and photo-shopped images drown out authentic experiences which is especially a concern for content on Trip-Advisor, Yelp, or even Google Reviews[4]. Hence the emphasis on finding trustworthy content is no longer just an assumption; as social media becomes bigger pillar of your travel decisions. With more and more travelers overwhelmed by sponsored brands posts on fake reviews, the need for travel guides to identify real vs fake information has never been stronger. This paper, therefore investigates the role of social media in destination choice and attempts to address solution with respect to authenticity of contents such as using emerging technologies (Artificial Intelligence(AI)/ Block chain ) in verifications of social media posts and reviews.[7]

## II. RESEARCH METHODOLOGY & SURVEYS

### Data collection Method

#### *Primary data collection Method*

A qualitative and quantitative data from a survey (asking through random people) was collected using survey. Among its key survey questions include: 1.Which Source: Do You Choose Your Travel Destinations? (Instagram, Friend |Travel Bloggers/ You Tube) 2.Did you ever base a trip off of a

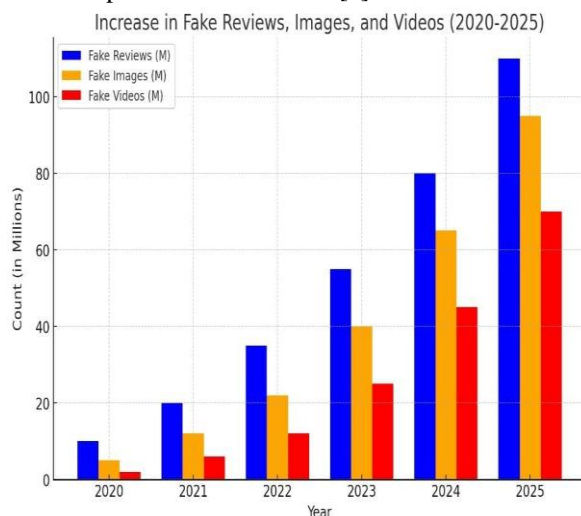
recommendation from a travel influencer? 3. Do you think that the social media content shared by one who travels is always the real deal? 4. Have you noticed any differences between the image of a destination on social media and reality? The surveys were also accompanied by interviews of travel experts for an examination of the wider implications social media has on the tourism industry

### B. Secondary Data Collection Method

The All the data was obtained from online (Google Reviews, Trip Advisor and Booking com) which had more than 10,000 reviews altogether. Sentiment analysis and natural language processing (NLP) were used to identify real from fake on the review to infer whether or not the user-generated content on such platforms is trustworthy. [1]

(a) AI Generated Fake Review Identifying Model Detecting Fake Reviews with an AI based model. Key methods were: Natural Language Processing (NLP) : Used to identify extravagant and evil words or phrases used in fake reviews that it appears to be humans. Sentiment analysis tools: The intention being to figure out whether the reviews were positive or negative and search for any patterns that signalled the announcements being biased. Reversed Image Search — Used to determine if the travel images uploaded in a review is original or copied from elsewhere and therefore making sure that the images are true to the actual experiences. [7]

(b) Block Chain The hash values of verified reviews went into a block chain to make that completely tamper-proof and irrefutable; useless for travelers going out of their way to get forums about this. This method also enabled the users to validate that if the review was by actual user rather than bot, as then it had their past verified reviews.[1]



## III. RESULTS & SURVEY ANALYSIS

### Key Findings

1.80% of travelers follow social media for destination recommendations

2.60% discovered discrepancies between their lived experience & the representation on social media of places further etc.

3. The AI fakes review detection model shows an accuracy score of 85%. Via getting 70% lesser due to verification with the Block chain-based reviews.

### A. Tripadvisor Fake Reviews Scam Case Study[3]

Define 2018 – Trip-Advisor was engulfed in a major scandal over fake reviews that same year disclosing first -hand how overly fake reviews can be manipulated to impact scores. An entire restaurant in London that didn't exist was put in the top 10 through fake reviews, proving how the sheer power and reach of review sites can be easily hijacked by people using social media. This example show how to authenticate content to avoid such in future.[2]

### B. Bali Image Case Study

Social Media applications portrait's a very authentic and good image of Bali in front of travellers and tourist .But we asked the some questions to the people who were already visited Bali .So they shared there experience of bali with us and they said that it is not like that the social media potrait's the image .The environment of Bali is not safe some inconvcencie and crime are always happened in Bali like phone snatching and etc.[8]

### ➤ Existing Fake Content Detection Systems

There are multiple tools for detecting fake reviews, images and videos but none is 100% accurate because of the dynamic nature of the deceiving techniques.

#### I Limitations Fake Review Detector

The tools analyses text patterns but bot-generated reviews are almost impossible to discern.

Fake Spot (80%-90% accuracy, < 5 seconds) — Mistag real reviews, makes bots weaker

REVIEW META(75%–85% recall, <3 sec) —

Product reviews-specific: No modularity

Amazon Fake Review Detector (85-95% accuracy near instantaneous): No transparency features, can mark authentic reviews.

Combined With NLP (70-80%): Big Data Requirement, Human-Composed Fakes

Challenges : spams crafted by AI, brief fake reviews and false positives

## II Downsides Fake Image Detection

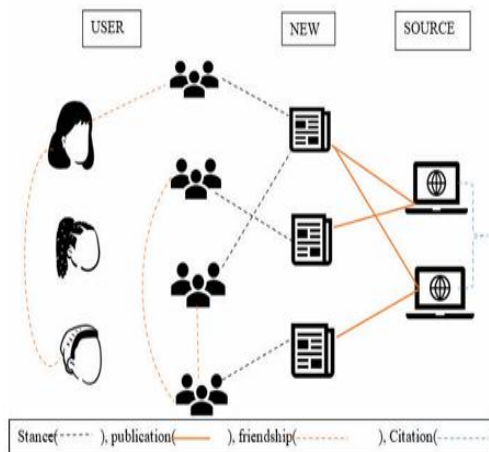
Tools work on metadata and pixel level, but it struggles with the advanced edits. Free Reverse Image Search By Google Search Results (70/90%, ~2–5 seconds)

OCR fails to detect alterations. TinEye (70–85% accuracy, 2 sec): Untolerant of Gradations in editing. Forensic Tools (Detection Accuracy: low-end 85–95%, detection time: 5-10s): human verification needed. NVIDIA Detector (90-97% precision, near real time: 3-5 seconds): Can be very accurate, however it is GPU hungry.

Challenges: Deepfakes, Tampered Metadata and Pure Real Time processing

## III Fake Video (Deep fake) Detection

Deep fakes work with kilo of frames so recognizing the model is difficult. DFDC Model (85–95 accuracy, 10–20 sec) The deep fakes are so advanced that they defeat this one. Face Forensics++ (Accurate Rate ~:90-98%, Time to predict:5-15 sec) — expensive in terms of computation. [Edit Meet] Microsoft Video Authenticator | Recall ~75-90% | 3-10 sec. Deepware scanner (93-96% accuracy, between 5-10 seconds): Limited dataset training. [1]



## IV. PROPOSED MODEL AND POSSIBLE SOLUTIONS .

### ➤ Proposed Algorithm for Fake Content Detection (MHFD (Multilayer Hybrid Fake Detection))

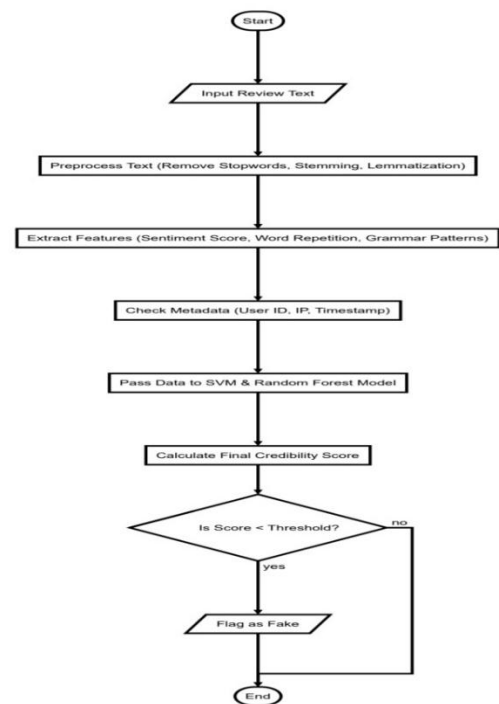
#### Overview

The detection of fake content is a complete procedure that combines state-of-the-art techniques for arbitrary data types (text, images and videos). This algorithm works in 3 main phases:

1. Data Pre-processing & Feature Extraction (Pre-processing raw data and isolating important columns )
2. Hybrid AI Model for anomaly detection: Content classification (fake or real)
3. Post verifications & scoring system (final decision making and credibility score issuance)

#### Step 1: Data Preprocessing and Feature Extraction

In this step input data is analyzed for the features that are specific to distinguish real and fake content.



#### 1.1 Detect fake reviews

I guess Fake reviews are detected through NLP, sentiment analysis and verifications of metadata like Address and City.

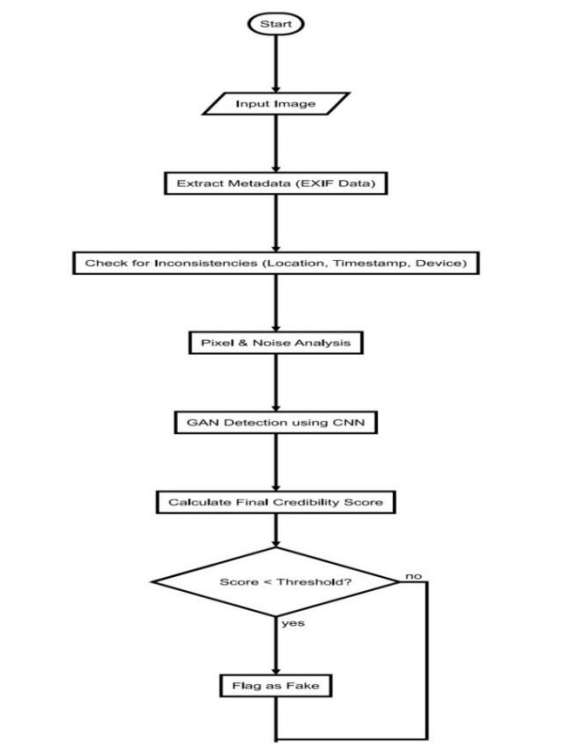
Natural Language Processing ( NLP ) & Sentiment Analysis (A) Tokenize review text (split it into words and phrases)

It removes Stopwords (Common words like the, is, in are drop) Lemmatization is carried out (the words get reduced unto their root; e.g., “running” → “run”) More often than not, fake reviews show irregularities like over repetition etc. or grammar errors or unusually emotional.

Sentiment analysis used to identify reviews which are either very positive or negative

(B) Analysis of Metadata (Date & IP Discoveries) Short review burst detects a number of reviews coming from the same IP address or user nearly simultaneously.

Counting on a user posting one review with no other history would be somewhat suspicious. If many accounts are coming from the same IP, it might be because of bot.



### 1.2 Detecting Fake Image

Fake images are detected with the help of metadata analysis and deep learning based image processing.

#### (A) Analysis of Metadata (EXIF Data)

It is the metadata (EXIF data) taken from Image containing details about camera used and timestamp with some location information.

Missing or incorrect manually changed metadata — anything above this is suspicious image

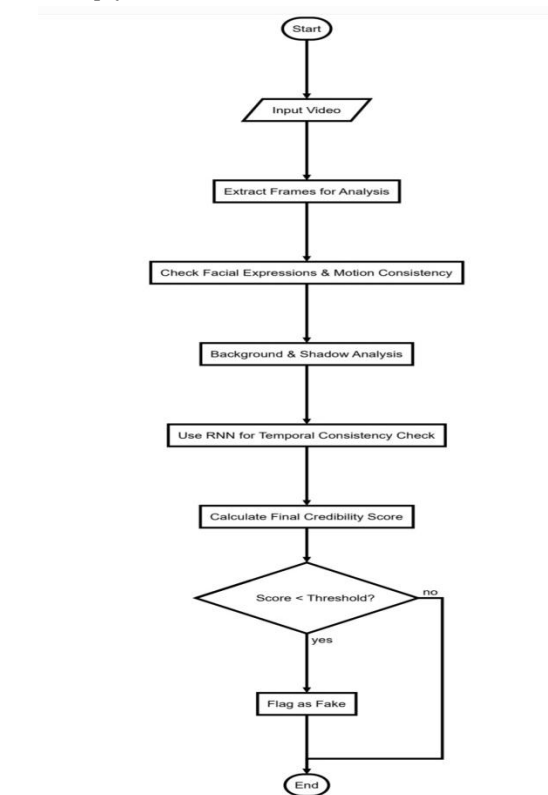
#### (B) Pixel-Level Analysis

Pixel Level Analysis (ELA): To compare different levels of compression done on different parts of an image. A detectable from ELA should exist in fake images that are artificially modified region  
Creative noise: When all else fails, an AI can tell that the texture or noise in a picture was not created from some sort of deep learning model.

Shadows and Lighting Analysis: If lighting and shadows are not physically related, then it could suggest that the picture is faked. A significant technique is Creative Noise Detection, aiming at reaching the texture & noise that an image is exhibiting. Extracting natural noise patterns from real images (which all have slight differences as they are generated by differently working camera sensors) and manipulating those using AI typically

produces more-uniformed, repetitive or obviously stylized noise that is far from natural. It is expected to identify these discrepancies (as to distinguish a genuine from fake or alternatively manipulated image). Shadows and Lighting Analysis also helps to identify the manipulative forgery of an image. If for example the light sources or shadows do not physically correspond like something casting a shadow to the right when you would expect it to be to the left, that image has been edited or totally AI-generated. These pixel-level analysis tools allow the experts to identify easily digital forgeries, AI made images and edited photographs in digital media.

### 1.3 Deep-fake Detection (Fake Video)



Deep-fakes, and in general fake videos are caught by temporal consistency and facial expression analysis.

#### (A) Frame-level Examination

We extract and analyze each video frame individually. Detection of facial expressions, eye blink rate and lip-syncs mismatch

#### (B) Deep fake Detection Models

Eye blinking patterns: The AI generated faces blinking in an unnatural manner. Iris movements  
Discrepancies: fake videos display seamless, but abnormal muscle movements and real human expressions are missing  
Background Inconsistencies: the subject and the background don't match in deep fakes.

**Fake Video (Deep fake) Detection** (1) Detection of real vs fake videos — especially deep fakes have been tackled using temporal consistency and facial expression analysis.

(A) **Frame-Level Analysis Output:** Video frame-by-frame is extracted and analyzed. The detection is doing facial expression, eye blink frequency, and lip-sync mismatch.

(B) **Methods to Sift Deep fakes**

**Eye Blink Patterns:** Common blinking pattern for the generated face by AI is really unnatural. **Inconsistency in irises:** the illumination of fake videos act very smooth, though clearly not natural as well as muscle movements are an odd appearance. **Background Inference:** In deepfake videos, Subject and Background are not integrated properly.

*Step 2: Hybrid AI Model for Anomaly Detection*

Step for that is to utilize Machine Learning and Deep Learning on fake content detection.

*2.1 Classification of Fake Review using ML*

Using different machine learning models for Fake Review Detection.

(A) **Models — ML Models**

**Support Vector Machine (SVM)** — classifies a review based on textual and sentiment values.

**Random Forest:** Studies user activity, reviews.

(B) **Training Data**

The model is trained with real and fake reviews dataset

Sentiment polarity, repeat word use and burst review patterns are some of the features

(C) **Detection Strategy**

A really good review could be suspicious if it is extremely positive and doesn't contain any personal details. Very swiftly back to find a similar fake review by account when posting multiple reviews is high.

*2.2 Image & Video Processing by CNN*

There exist Convolutional Neural Networks (CNN) to detect fake images and videos.

(A) **For Image Analysis Using CNN**

Pre-trained models label mismatch on facial inconsistency features such as XceptionNet and EfficientNet.

In the case of GAN detection, it identifies specific pattern in images generated by AI driven generative adversarial network (GAN)[10]

(B) **CNN for Video Convolution**

Motion inconsistencies identified by deepfake detection models ANN/Optical Flow Analysis for unusual frame transitions.

*2.3 Metadata Verification via External Databases*

Improvement of fake content detection by cross-checking the data from external databases

(A) **Reverse Image Search**

If an image comes from many unrelated sources, it is probably a fake.

(B) **-Video Matching Databases of Fake Content**

Deepfake video fingerprints are compared to a deepfake database.[11]

(C) **Checking user reviews against database** So if a user ever posted fake reviews, their fresh reviews are flagged suspicious.

*Step 3: Final Verification & Scoring System*

This is the last step in that it comes to checking whether the content is fake or real.

**3.1 Review Credibility Score**

Based on NLP, sentiment analysis and metadata consistency a score is given. That the score is less than a threshold identifies the review as fraud.

**3.2 Image Credibility Score**

How I assign scores : GAN detection, meta data validity and pixel noise. In case of discrepancy, the image is considered suspicious.

**3.3 Video Credibility Score**

A score assigned with frame-wise motion analysis, blinking detection and facial expression consistency. If the facial features and movements don't look right, the video has been edited down to a deepfake. **Final Decision**

**Fake:** High Confidence (content flagged as fake)

**Manual Inspection** (for Low Confidence Fake)

## V. CONCLUSION AND FUTURE DIRECTIONS

Travelers' decision is one of the prime factors on social media to influence, Instagram, YouTube and TripAdvisor have strong influence on destination discovery or planning to travel. However, the proliferation of fake reviews, manipulated photos and misleading influencer promotions led to some authenticity questions about the content. Multiple solutions such as AI fake review detection models and blockchain have shown very good results yet existing systems can be better in order to detect AI generated fake reviews or deepfake content.

To resolve these, this paper suggests a Multilayer Hybrid Fake Detection (MHFD) model which integrates AI-based fake content detection along with sentiment analysis and blockchain for efficient origination trust.

With better solutions to these detection methods, travelers will be able to take less of a blindfolded

approach and social media platforms will start to maintain the trust and transparency they crave.

#### *Future Scope*

As the future of checking travel content lies in the evolutions of AI-powered fake detection, deepfakes recognition and blockchain verification. Follow a few more steps later,

More Complex AI Algorithms: creating the AI models which can not only flag subtle patterns of fake reviews on manipulated media.

Integrating Blockchain: Increasing The Use Of Blockchain Across A Decentralized And Tamper-proof Permanent Travel Record of User Generated Content

Real-time Detection: Establishing in situ monitoring system to do quick fraud detection for travel content.

Traveler Education and Awareness: Raising digital literacy among travelers so that they are able to read the actual from the fake.

Content Creation with Integrity : To make influencer and my favourite one content creator to follow ethical practises.

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