

# Fake Job Listing Detection

Deep Learning & Agentic Generative AI

MILESTONE 1 REPORT

# The Current Landscape: A Crisis of Trust

## FTC Warns of Surge in Fake Job Scams

NYTimes.com - Oct 24, 2023

Agency reports record complaints as scammers exploit remote work trends...



## Thousands Fall Victim to LinkedIn Phishing Attacks



TechCrunch - Nov 15, 2023

Malicious actors impersonate recruiters to steal personal data and credentials...

## The 'Ghost Job' Problem: Why Your Application is Ignored



Forbes - Dec 1, 2023

Many listings are fake or inactive, used for market research or data collection...

## How Scammers Use AI to Create Convincing Job Posts



Wired - Dec 12, 2023

Generative AI tools are making it easier to create highly targeted and believable fraudulent listings...

## New Report: Financial Losses from Job Fraud Hit Record High



FBI.gov - Jan 5, 2024

Victims report significant monetary losses through advance-fee fraud and identity theft...

Widespread fraud. Financial impact. Eroding confidence.

# Why Current Defenses Fail



Easily Bypassed



Misses Context



The Black Box

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We need verification, not just classification.

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# THE DETECTION LANDSCAPE: FIVE APPROACHES

01

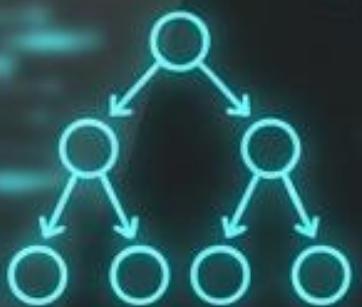
RULE-BASED



**Keyword Filtering.**  
Simple matching,  
easily bypassed.

02

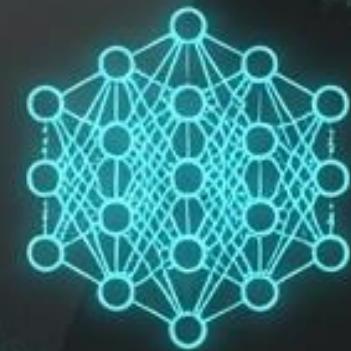
CLASSICAL ML



**Naive Bayes / Random Forest.**  
Uses TF-IDF  
features.

03

DEEP LEARNING



**CNN / LSTM.**  
Better context,  
black box.

04

TRANSFORMERS



**BERT / RoBERTa.**  
State-of-the-art  
text understanding.

05

EXPLAINABLE AI



**LIME / SHAP.**  
Feature weights,  
not user  
explanations.

# Performance Leaderboard

Transformers define the current ceiling for text accuracy

## Model Approach

Rule-Based (Keyword Filter)	<div style="width: 10%;"> </div>	Accuracy: Low   F1: Low
Classical ML (Random Forest)	<div style="width: 97%;"> </div>	Accuracy: 97%   F1: 0.82
Deep Learning (BiLSTM)	<div style="width: 97%;"> </div>	Accuracy: 97%   F1: 0.83
Transformer (BERT)	<div style="width: 98%;"> </div>	Accuracy: 98%   F1: 0.88
Transformer (RoBERTa)	<div style="width: 98.5%;"> </div>	 <b>Best Baseline</b> Accuracy: 98.5%   F1: 0.91

# THE BLIND SPOT: WHY HIGH ACCURACY ISN'T ENOUGH

Critical weaknesses in existing approaches.



## NO METADATA VERIFICATION

Models ignore email domains, missing info, and salary ranges.



## BLACK BOX PREDICTIONS

Outputs a score without explanation. Hard to trust.



## POOR CLASS IMBALANCE HANDLING

Only ~4.8% of listings are fake; models miss fraud cases.



## NO HUMAN-READABLE EXPLANATION

LIME/SHAP provide numbers, not plain-language reports.

# Gap Analysis

Fractures in current defenses

Gap 1: No multi-step verification  
(Domain/Salary ignored)

Gap 2: No narrative explanation  
(Just scores)

Gap 3: Metadata is ignored (Email/Location missing)

Gap 4: Class imbalance unresolved  
(Low recall)



# Bridging the Gaps: The Proposed System

**RoBERTa  
Classifier**

Fixes: Text Understanding

Fine-tuned transformer achieves ~98.5% accuracy.

**Agentic  
Verification**

Fixes: Multi-step Reasoning

Checks company domain, email pattern, and salary.

**Generative AI  
Layer**

Fixes: Human-Readable Report

Produces a plain-language fraud report.

**Text + Metadata  
Pipeline**

Fixes: Ignoring Metadata

Combines text signals and structured data.

# Key Differentiators

Feature	Traditional ML	Deep Learning	Proposed System
Context Understanding	Low	High	High 
Metadata Verification	No 	No 	Yes 
Multi-step Reasoning	No 	No 	Yes 
Structured Explanation	No 	Limited	Yes 
Agent-Based System	No 	No 	Yes 

# A Hybrid Approach



Transformer  
Models

Agentic  
Verification

Trust &  
Explainability

Combining RoBERTa for text understanding with Agents for fact-checking.

# Project Context & Importance.

## Why Fraud Detection Matters



Financial Loss



Identity Theft



Reputational Damage

## Stakeholders



Job Seekers



Employers

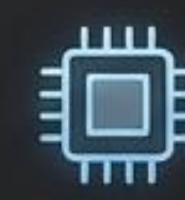


Platforms

## Current Status of Job Scams



Increasing Volume



Higher Sophistication



Low Detection Rate

## Scope & Boundaries

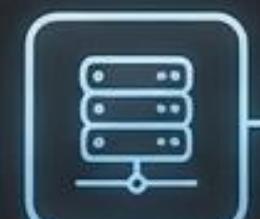
### In-Scope

- Text Analysis
- Salary Verification
- Domain Checks

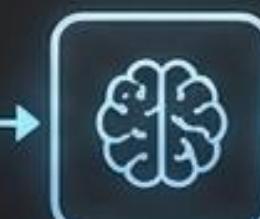
### Out-of-Scope

- Legal Action
- Dark Web Monitoring
- Physical Verification

## Project Analysis



Data Collection



Model Training



Testing & Validation



Deployment

Addressing the urgent need for advanced fraud detection mechanisms.

# The Agentic Workflow



Multi-step reasoning to cross-check suspicious attributes.

# Not Just a Score. A Story.

Generative AI provides structured, plain-language warnings.



# Target Objectives: Robust Multi-Step Verification & Use Case



**Raw Data**

**Multi-Step Verification**  
(Domain, Salary, Metadata)

**Robust Prediction Model**

**Real-world Use Case**  
(e.g., Fraud Detection)



Target Accuracy  
**95%**



F1-Score  
**>0.90**



**3+**  
Verification Tools Integrated



**EMSCAD**  
Benchmark Dataset

# The Builders (Milestone 1)

Arun Dutta

Literature Review & Gap Analysis

- State-of-the-art methods (SOTA)
- Identify existing dataset limitations

Hritik Roshan Maurya

Problem Framing & System Architecture

- Define problem scope and objectives
- Architectural diagram & module breakdown

Vivek Bajaj

Data Pipeline & Deep Learning Workflow

- Data cleaning, preprocessing, & augmentation
- Model selection, training, & hyperparameter tuning

Vishwas Mehta

Fraud Pattern Analysis & Domain Research

- Analyze common fraud tactics
- Consult with domain experts for feature engineering

# Status & Next Steps



Moving from architecture to implementation.