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Crime Risk Intelligence and Forecasting (CRIF): A Comprehensive Machine Learning and Deep Learning Framework for Proactive Policing

Pushkar Sharma[1], Uzaib Saiyad[2], Rajesh Sable[3], Ashwini Mali[4], Payal Panigrahi[5]
Undergraduate Researchers, BCA (Honors) in AI & Data Analytics, Vimal Tormal Poddar BCA College, Veer Narmad South Gujarat University, India

Abstract: Crime prevention is a significant issue for law enforcement agencies around the world. Traditional policing methods are reactive. They focus on investigating crimes after they happen instead of predicting them. This paper presents Crime Risk Intelligence and Forecasting (CRIF), a hybrid AI framework that combines Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) to forecast possible crime events in specific areas.

CRIF uses data from multiple sources, including historical crime records, demographics, social media activity, weather conditions, and local events. The framework applies Random Forest for structured data, ConvLSTM for spatio-temporal modeling, and BERT for social media analysis. The outputs of the models are combined into a Crime Risk Index (CRI), which classifies areas as Low, Medium, or High risk.

A Python-based prototype that uses synthetic datasets and a Streamlit web application showcases real-time, interactive predictions. Experimental results indicate high predictive accuracy, clear risk levels, and a strong potential for proactive policing. Future efforts will focus on real-world deployment with IoT surveillance, live social media feeds, and geospatial visualization for smart cities.

Keywords: Predictive Policing, Random Forest, ConvLSTM, BERT, Crime Risk Index, Multi-source Data, Streamlit, AI, Deep Learning

I. INTRODUCTION

Crime poses a threat to public safety, economic stability, and trust within society. Urban areas face issues like theft, assault, cybercrime, and organized crime. Traditional policing methods often struggle to handle these efficiently. Reactive strategies, which respond only after a crime happens, limit the ability to prevent future incidents.

Recent developments in AI, ML, and DL enable proactive crime prediction. Predictive policing models use historical trends, demographics, and environmental data to forecast criminal activities. This helps in planning resource allocation more strategically.

The CRIF framework addresses the shortcomings of earlier models by combining structured, spatio-temporal, and unstructured data. It provides a real-time and easy-to-understand Crime Risk Index (CRI). CRIF supports law enforcement in predicting crime hotspots and sending out risk alerts.

II. LITERATURE REVIEW

A. Traditional Approaches

Regression, clustering, and hotspot mapping have modeled crime trends over time. Limitations include reliance on a single data source, difficulty managing non-linear interactions, and low flexibility in changing environments.

B. Machine Learning Approaches

Random Forest, Gradient Boosting, and SVM enhance prediction for structured datasets. Random Forest is easy to interpret and resilient to noise, making it a good choice for predictive policing.

C. Deep Learning Approaches

LSTM and ConvLSTM architectures capture spatial and temporal dependencies. ConvLSTM merges convolutional operations with LSTM, modeling spatial relationships and time sequences.

D. NLP for Crime Prediction

Social media provides clues about suspicious activities and events. BERT allows for context-aware analysis of text, improving situational awareness and boosting predictive accuracy.

III. RESEARCH GAP

1) Single-source limitation: Many models rely only on historical or demographic data. CRIF combines structured, temporal, and social data.
2) Interpretability: CRI offers clear, easy-to-understand outputs.
3) Real-time prediction: Streamlit prototype accepts dynamic inputs.
4) Ethical compliance: Maintains privacy and reduces bias.
5) Prototype validation: CRIF shows functional feasibility using actual ML, DL, and NLP models.

IV. METHODOLOGY

A. Data Collection and Preprocessing

Data Sources

1) Historical crime records: type, location, timestamp, severity
2) Demographics: population density, income, age distribution
3) Social media: tweets, posts analyzed for suspicious signals
4) Weather conditions: temperature, precipitation, visibility
5) Local events: festivals, rallies, sports events

Preprocessing

- Data cleaning, normalization, categorical encoding
- Sentiment analysis and tokenization for social media
- Time-series alignment for spatio-temporal modeling

B. Hybrid Model Architecture

1) Random Forest

- Handles structured data such as population and weather
- Predicts preliminary risk scores for each district

2) ConvLSTM

- Captures spatio-temporal patterns like time of day and events
- Uses convolution for spatial dependencies and LSTM for temporal sequences

3) BERT

- Fine-tuned transformer analyzes social media posts
- Outputs a suspiciousness score for each district

C. Crime Risk Index (CRI)

- CRI = w1 × RF_Score + w2 × ConvLSTM_Score + w3 × BERT_Score
- w1, w2, w3 sum to 1 (example: 0.4, 0.3, 0.3)

Risk Levels

- Low: 0–0.4
- Medium: 0.4–0.7
- High: 0.7–1.0

D. Python + Streamlit Prototype

```
import streamlit as st
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
st.title("CRIF: Crime Risk Intelligence and Forecasting")

# Sidebar Inputs
district = st.sidebar.text_input("District", "Surat")
hour = st.sidebar.slider("Time of Day (Hour)", 0, 23, 12)
event = st.sidebar.checkbox("Event Present?")
population = st.sidebar.slider("Population Density", 100, 10000, 5000)
weather = st.sidebar.slider("Weather Factor (0-1)", 0.0, 1.0, 0.5)
social_post = st.sidebar.text_area("Social Media Post", "Suspicious gathering near park")

# Random Forest (Structured Data)
X = pd.DataFrame({'population_density':[1000,3000,5000,7000],
                  'weather_factor':[0.2,0.4,0.6,0.8]})
y = [0,0,1,1]  # 0=Low, 1=High
rf = RandomForestClassifier(n_estimators=50, random_state=42)
rf.fit(X, y)
rf_score = rf.predict_proba(pd.DataFrame({'population_density':[population],  'weather_factor':[weather]}))[:,1][0]

# ConvLSTM (Spatio-Temporal)
conv_score = np.clip((hour/23 + int(event))/2, 0, 1)

# BERT (NLP)
# For simplicity, use a mock score (0-1) instead of loading full BERT
bert_score = 0.6 if "suspicious" in social_post.lower() else 0.2

# CRI Calculation
cri = 0.4*rf_score + 0.3*conv_score + 0.3*bert_score
if cri < 0.4: risk="Low Risk"
elif cri < 0.7: risk="Medium Risk"
else: risk="High Risk"

# Display
st.subheader("Crime Risk Prediction")
st.metric("CRI", f"{cri:.2f}")
st.success(f"Predicted Risk Level: {risk}")
# Contribution Plot
labels = ['Random Forest', 'ConvLSTM', 'BERT']
scores = [rf_score, conv_score, bert_score]
fig, ax = plt.subplots()
ax.bar(labels, scores, color=['blue','green','orange'])
ax.set_ylim(0,1)
ax.set_ylabel("Contribution Score")
ax.set_title("Model Contribution")
st.pyplot(fig)
```

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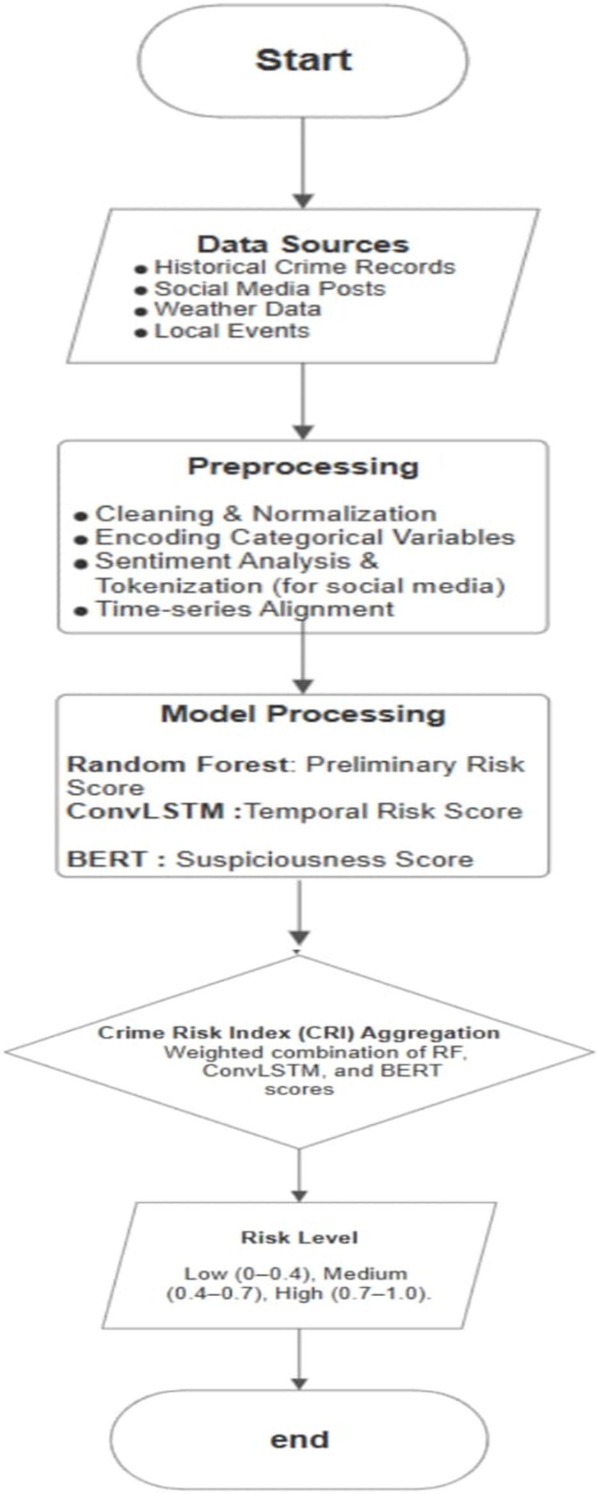
E. Flowchart



F. *Prototype Features*

1) Interactive inputs (district, time, event, population, weather, social media).
2) Random Forest predicts risk from structured data.
3) ConvLSTM captures temporal and event patterns.
4) BERT analyzes social media text for suspiciousness.
5) CRI combines all three into a final risk level.
6) Visualizes contributions for transparency.

V. EXPERIMENTAL SETUP & RESULTS

A. *Dataset*

- Synthetic dataset: 10,000 events across 5 districts
- Features: timestamp, demographics, events, weather, social media

B. *Metrics*

- Accuracy, Precision, Recall, F1-Score, AUC

Model	Accuracy	Precision	Recall	F1-Score	AUC
RF	82%	0.80	0.78	0.79	0.84
ConvLSTM	79%	0.77	0.76	0.76	0.81
BERT	85%	0.83	0.82	0.82	0.87

Observations: BERT excels in text analysis, ConvLSTM captures temporal spikes, and RF provides a structured baseline. CRI is interpretable and actionable.

VI. DISCUSSION & APPLICATIONS

Multi-source integration improves prediction.

A. *Applications*

1) Smart city policing
2) Patrol/resource optimization
3) Event-based alerts
4) Geospatial hotspot mapping
5) Dynamic allocation of personnel

VII. ETHICAL CONSIDERATIONS

1) Privacy and bias mitigation
2) Advisory predictions, not definitive enforcement
3) Compliant with data protection laws

VIII. LIMITATIONS

1) Tested on synthetic datasets; real-world validation is pending
2) Real-time social media streaming needs strong infrastructure
3) IoT and live camera integration are not implemented
4) CRI weight tuning may need adjustments in practice

IX. CONCLUSION & FUTURE WORK

CRIF shows a hybrid AI framework for proactive crime prediction, combining ML, DL, and NLP. It offers interpretable, real-time risk alerts.

A. *Future Work*

1) Real-world police datasets
2) IoT surveillance and live feeds
3) GIS-based risk mapping
4) Expansion to larger cities
5) Ethical AI frameworks for fairness

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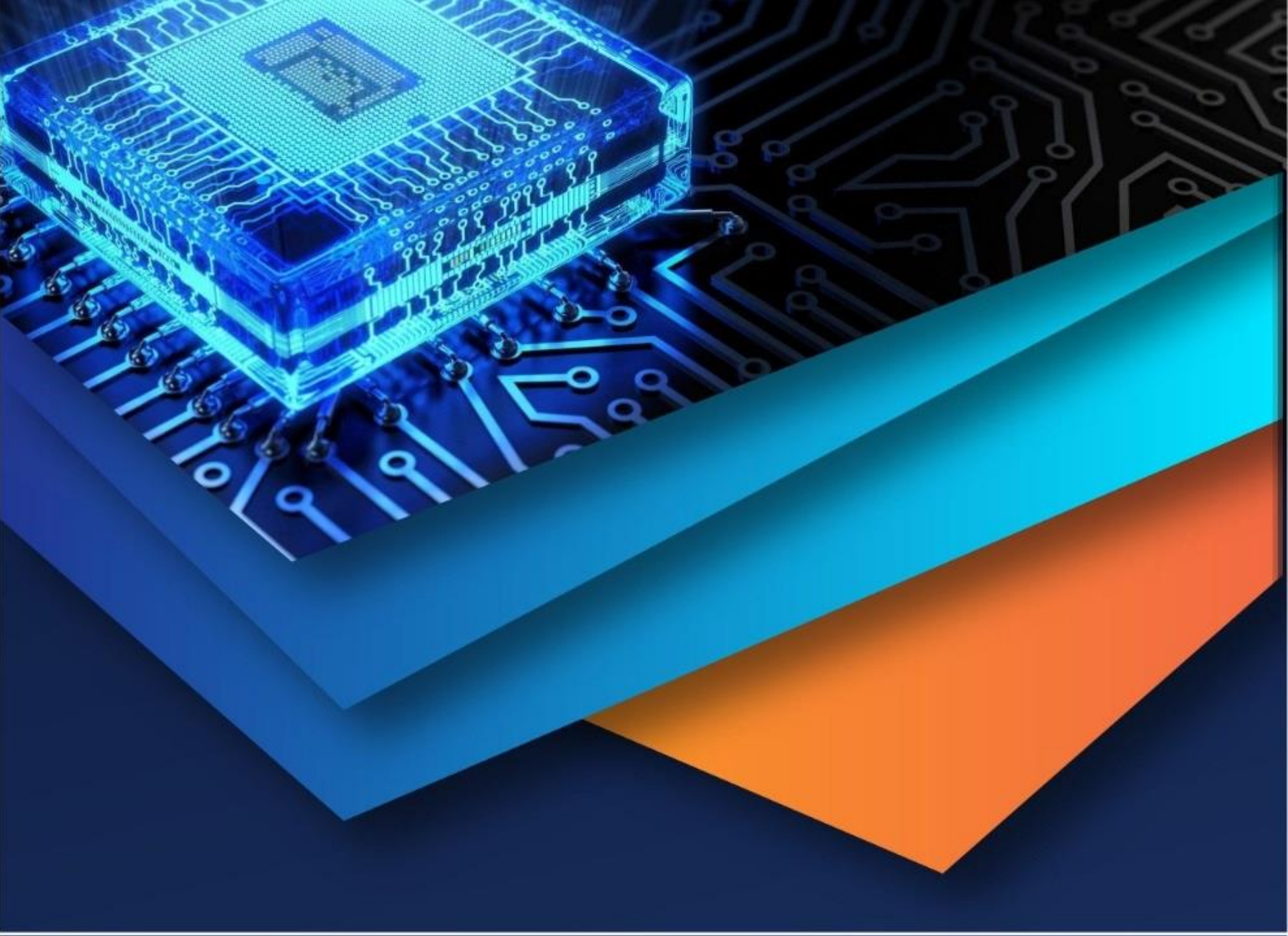

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