IEEE RESEARCH PRESENTATION

AI-Based Rockfall Prediction & Alert System

A TEMPORAL DEEP LEARNING APPROACH FOR OPEN-PIT MINE SAFETY

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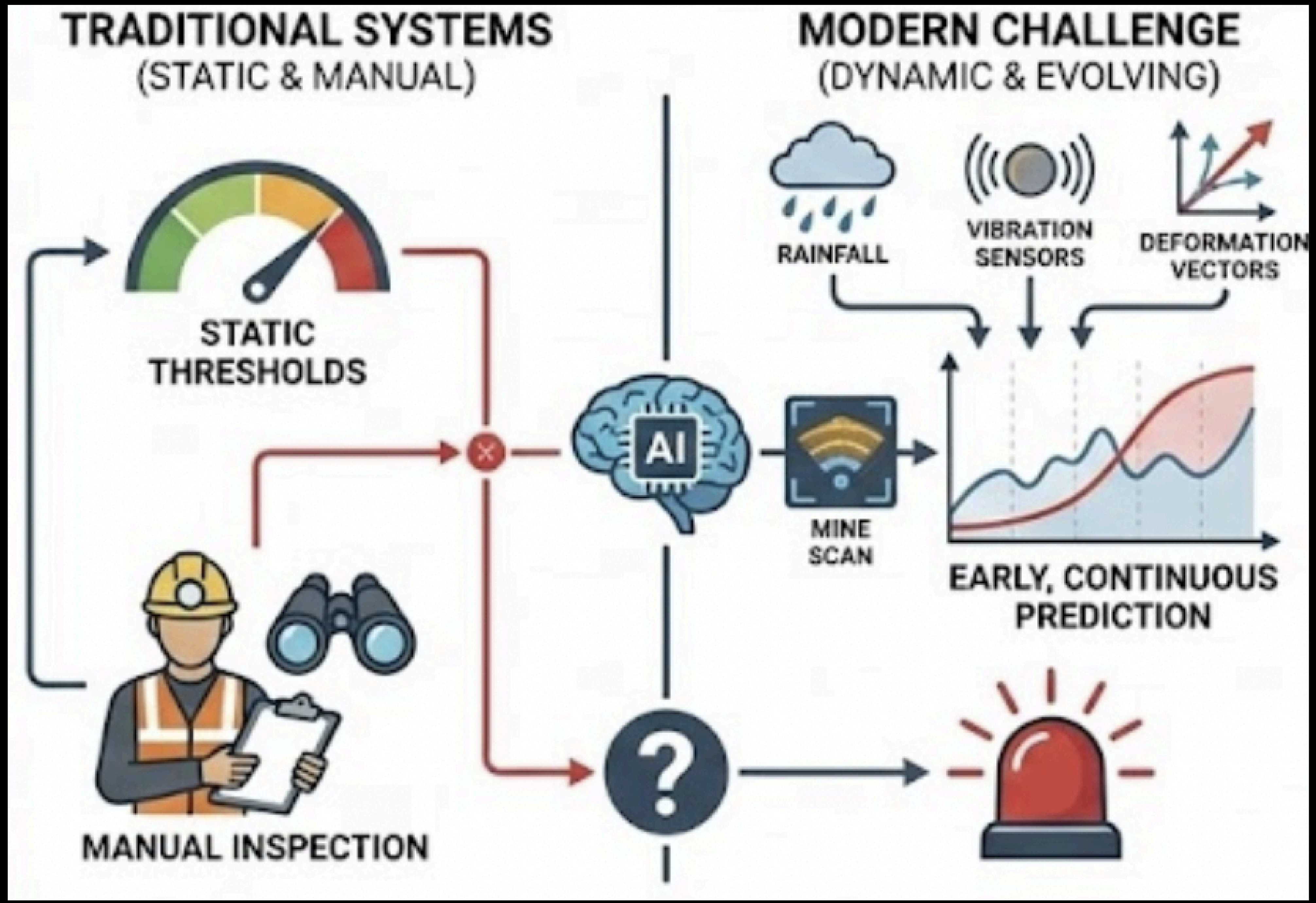
PROBLEM STATEMENT

- OPEN-PIT MINES FACE FREQUENT ROCKFALL AND SLOPE INSTABILITY RISKS
- TRADITIONAL SYSTEMS RELY ON STATIC THRESHOLDS AND MANUAL INSPECTION
- MINE CONDITIONS EVOLVE DYNAMICALLY DUE TO RAINFALL, VIBRATION, AND DEFORMATION
- SNAPSHOT-BASED ML MODELS FAIL TO CAPTURE TEMPORAL RISK PROGRESSION
- EARLY, CONTINUOUS RISK PREDICTION REMAINS A CRITICAL CHALLENGE



RESEARCH GAP & OBJECTIVES

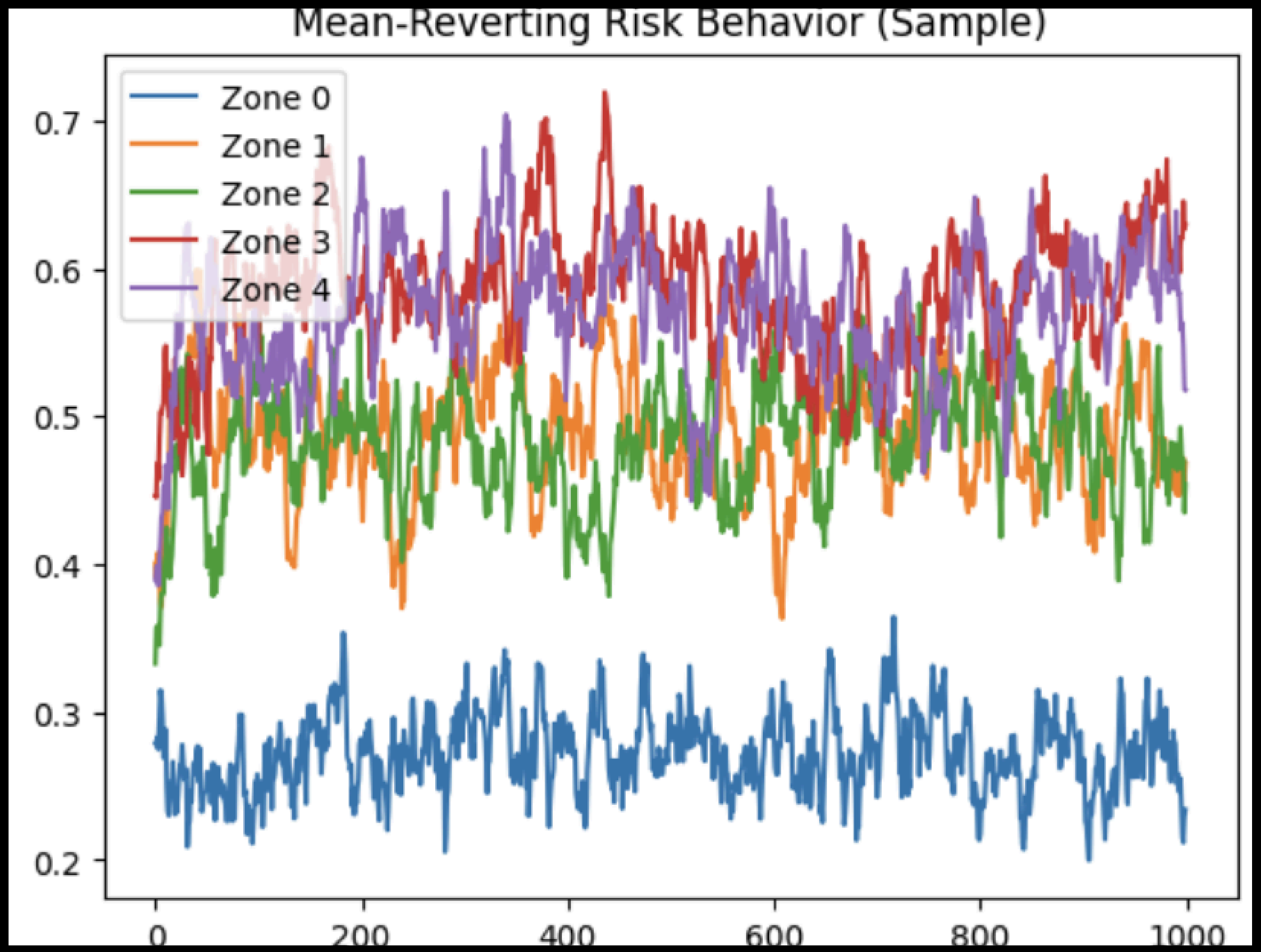
RESEARCH GAP

- EXISTING MONITORING SYSTEMS RELY ON STATIC THRESHOLDS AND MANUAL INTERPRETATION
- CLASSICAL ML APPROACHES MODEL RISK AS ISOLATED SNAPSHOTS, FAILING TO CAPTURE TEMPORAL EVOLUTION
- LIMITED INTEGRATION OF PREDICTION, ALERTING, AND VISUALIZATION INTO ONE SYSTEM
- LACK OF REALISTIC DATASETS CAPTURING DYNAMIC MINE BEHAVIOR OVER TIME

OBJECTIVES OF THIS WORK

- DEVELOP A REALISTIC TEMPORAL RISK DATASET FOR OPEN-PIT MINE SAFETY
- DESIGN A DEEP LEARNING MODEL (LSTM) TO CAPTURE RISK EVOLUTION OVER TIME
- IMPLEMENT A DYNAMIC RISK SCORING AND ALERT
- DEPLOY AN INTERACTIVE DASHBOARD FOR REAL-TIME DECISION SUPPORT

DATASET DESIGN & CHARACTERISTICS



ZONE-WISE MEAN-REVERTING TEMPORAL RISK BEHAVIOR IN THE SYNTHETIC DATASET

DATASET OVERVIEW

- LARGE-SCALE SYNTHETIC TEMPORAL DATASET DESIGNED TO SIMULATE OPEN-PIT MINE SLOPE BEHAVIOR
- 50,000 TIME-INDEXED SAMPLES ACROSS 5 DISTINCT MINE ZONES
- EACH SAMPLE REPRESENTS CONTINUOUS MULTI SENSOR-DRIVEN MONITORING

MONITORED FEATURES

- SURFACE DISPLACEMENT
- INTERNAL STRAIN
- PORE WATER PRESSURE
- MICRO-SEISMIC VIBRATION
- RAINFALL INTENSITY
- AMBIENT TEMPERATURE

ZONE-SPECIFIC BEHAVIORAL MODELING

- ZONE 0: MOSTLY STABLE BASELINE BEHAVIOR
- ZONE 1: RAINFALL-SENSITIVE INSTABILITY PATTERNS
- ZONE 2: VIBRATION-DOMINATED RISK FLUCTUATIONS
- ZONE 3: SLOW CREEP AND PROGRESSIVE DEFORMATION
- ZONE 4: MIXED AND UNPREDICTABLE CONDITIONS

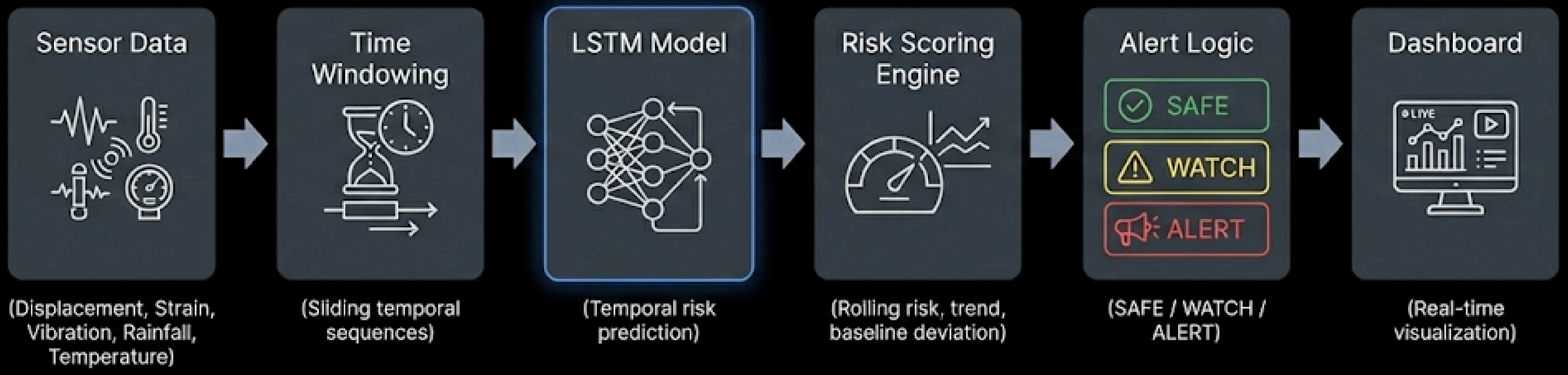
TARGET VARIABLE

- CONTINUOUS RISK INDEX $\in [0, 1]$
- CAPTURES SMOOTH TRANSITIONS BETWEEN:
  - NORMAL
  - STRESSED
  - CRITICAL STATES

METHODOLOGY & SYSTEM ARCHITECTURE

SYSTEM WORKFLOW

- MULTI-SOURCE SENSOR DATA COLLECTED CONTINUOUSLY OVER TIME
- TEMPORAL SEQUENCES CONSTRUCTED USING SLIDING TIME WINDOWS
- LSTM-BASED DEEP LEARNING MODEL PREDICTS FUTURE RISK INDEX
- DYNAMIC RISK SCORING AND TREND ANALYSIS PERFORMED
- ALERTS GENERATED BASED ON RISK LEVE AND PERSISTENCE
- RESULTS VISUALIZED THROUGH AN INTERACTIVE DASHBOARD

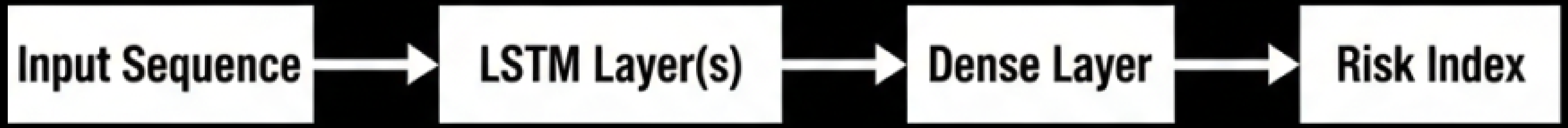


END-TO-END SYSTEM ARCHITECTURE

LSTM MODEL ARCHITECTURE & TRAINING

MODEL ARCHITECTURE

- TEMPORAL SEQUENCES CONSTRUCTED USING SLIDING WINDOWS (30 TIMESTEPS)
- INPUT FEATURES: DISPLACEMENT, STRAIN, PORE PRESSURE, VIBRATION, RAINFALL, TEMPERATURE
- LSTM NETWORK CAPTURES LONG-TERM TEMPORAL DEPENDENCIES
- FULLY CONNECTED OUTPUT LAYER PREDICTS CONTINUOUS RISK INDEX $\in [0, 1]$



LSTM-BASED TEMPORAL RISK PREDICTION ARCHITECTURE USED IN THIS WORK.

TRAINING STRATEGY

- SUPERVISED LEARNING USING MSE LOSS OPTIMIZED WITH ADAM
- TRAIN–TEST SPLIT ENSURES ZONE-WISE GENERALIZATION
- EARLY STOPPING APPLIED TO PREVENT OVERFITTING

BASELINE MODELS & PERFORMANCE COMPARISON

BASELINE MODELS CONSIDERED

1. LINEAR REGRESSION (LR)
   - SIMPLE STATISTICAL BASELINE
   - ASSUMES LINEAR RELATIONSHIPS
   - NO TEMPORAL MEMORY

2. RANDOM FOREST REGRESSOR (RF)
   - NONLINEAR ENSEMBLE METHOD
   - CAPTURES FEATURE INTERACTIONS
   - SNAPSHOT-BASED PREDICTION

PROPOSED LSTM MODEL

- TEMPORAL DEEP LEARNING ARCHITECTURE
- CAPTURES LONG-TERM DEPENDENCIES
- DESIGNED FOR CONTINUOUS RISK EVOLUTION

Prediction Accuracy Comparison

Model	MAE ↓	RMSE ↓
Linear Regression	0.0221	0.0278
Random Forest	0.0310	0.0389
LSTM (Proposed) ✓	**0.0190**	**0.0240**

TEMPORAL MODELING SIGNIFICANTLY IMPROVES PREDICTION ACCURACY OVER STATIC BASELINES.

💡TREE-BASED MODELS CAPTURE NONLINEARITY BUT FAIL TO MODEL TEMPORAL DEPENDENCIES.

PERFORMANCE COMPARISON BETWEEN BASELINE MACHINE LEARNING MODELS AND THE PROPOSED LSTM FRAMEWORK.

RISK SCORING, ALERT LOGIC & THRESHOLDING

DYNAMIC RISK SCORING

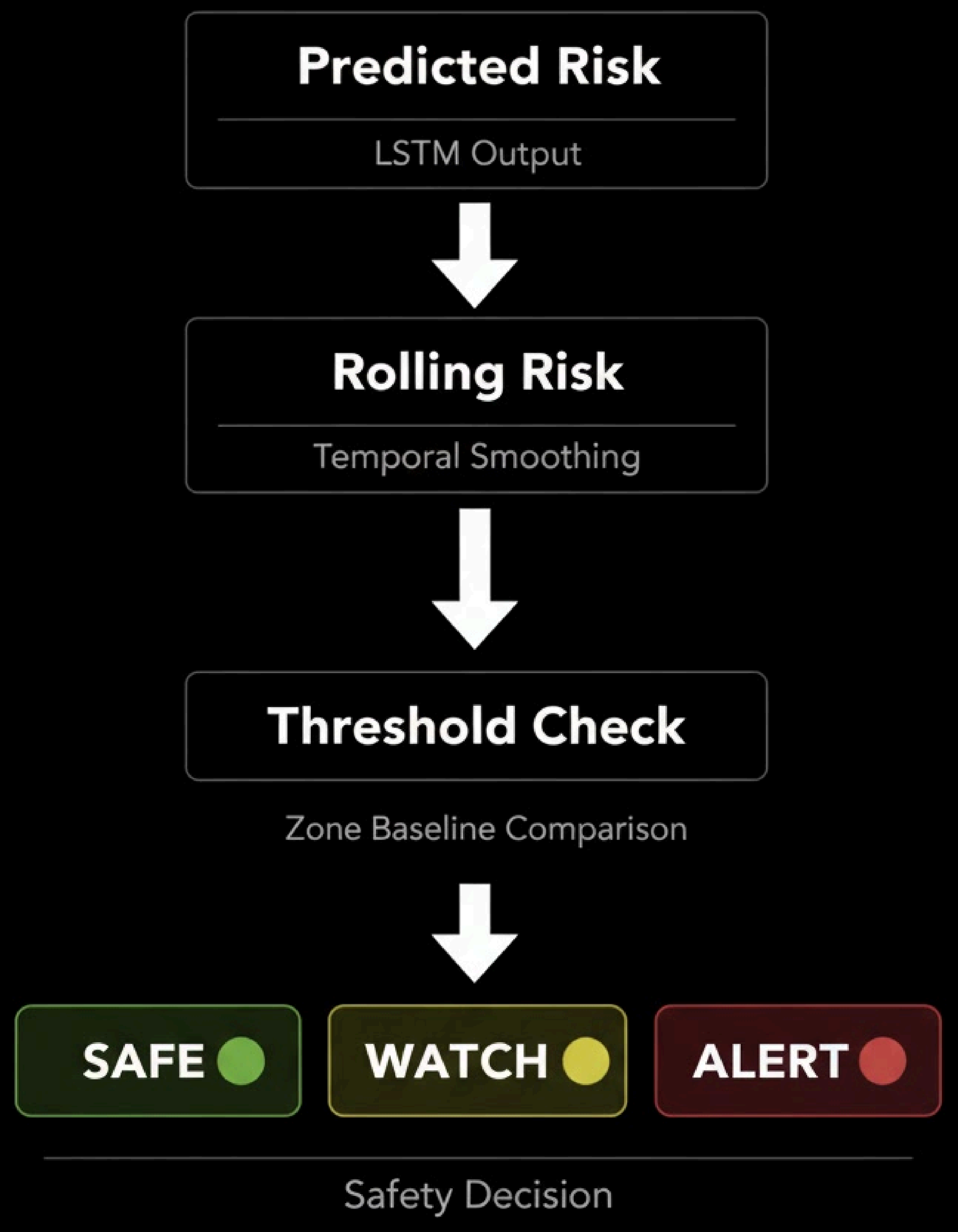
- LSTM OUTPUTS A CONTINUOUS RISK INDEX IN THE RANGE [0, 1]
- ROLLING RISK COMPUTED USING A TEMPORAL SMOOTHING WINDOW
- RISK TREND AND DEVIATION FROM ZONE-SPECIFIC BASELINE MONITORED
- ENABLES EARLY DETECTION OF GRADUAL INSTABILITY PATTERNS

ALERT THRESHOLDING STRATEGY

- SAFE: RISK BELOW BASELINE + TOLERANCE MARGIN
- WATCH: RISK RISING ABOVE BASELINE WITH POSITIVE TREND
- ALERT: SUSTAINED HIGH RISK EXCEEDING ZONE-SPECIFIC CRITICAL THRESHOLD

PERSISTENT ALERT LOGIC

- ALERTS TRIGGERED ONLY IF RISK REMAINS ELEVATED FOR MULTIPLE TIMESTEPS
- REDUCES FALSE POSITIVES CAUSED BY TRANSIENT SENSOR NOISE
- ENSURES RELIABLE, OPERATOR-TRUSTWORTHY WARNINGS



DYNAMIC RISK SCORING AND ALERT GENERATION PIPELINE

EXPERIMENTAL RESULTS & VALIDATION

PREDICTION ACCURACY EVALUATION

- EVALUATED ON HELD-OUT TEST SET ACROSS ALL MINE ZONES
- METRICS USED: MAE AND RMSE (LOWER IS BETTER)
- LSTM MODEL CONSISTENTLY OUTPERFORMS BASELINE METHODS

Prediction Accuracy Comparison

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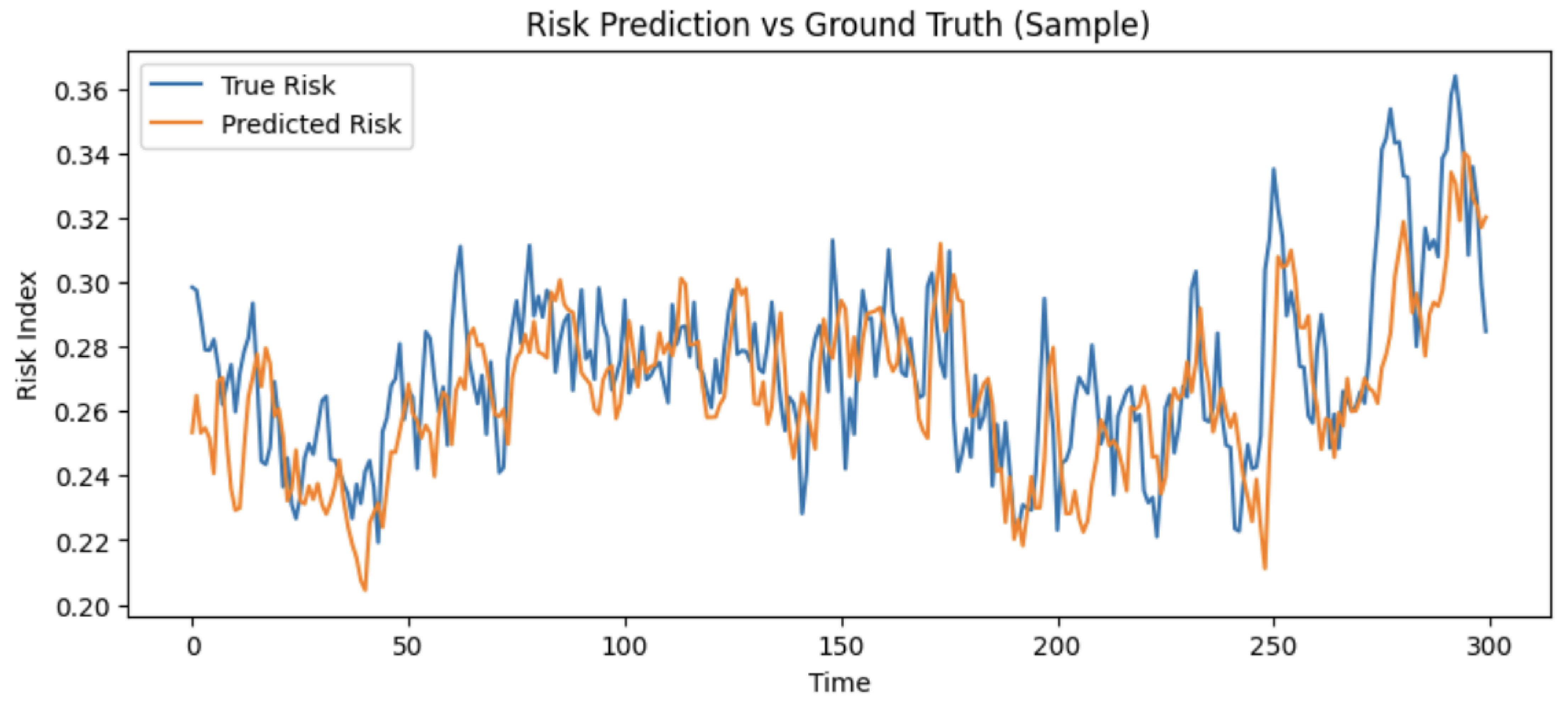
Linear Regression	0.0221	0.0278
Random Forest	0.0310	0.0389
LSTM (Proposed) ✓	**0.0190**	**0.0240**

KEY OBSERVATIONS

- LSTM CAPTURES SMOOTH TEMPORAL RISK EVOLUTION WITHOUT NOISY FLUCTUATIONS
- PREDICTION ERRORS REMAIN CONSISTENTLY LOW ACROSS ZONES
- TEMPORAL MODELING SIGNIFICANTLY REDUCES FALSE ALARMS COMPARED TO STATIC MODELS
- RESULTS CONFIRM SUITABILITY FOR REAL-TIME MINE SAFETY MONITORING



PREDICTED RISK CLOSELY FOLLOWS GROUND TRUTH ACROSS TIME, VALIDATING TEMPORAL LEARNING CAPABILITY.

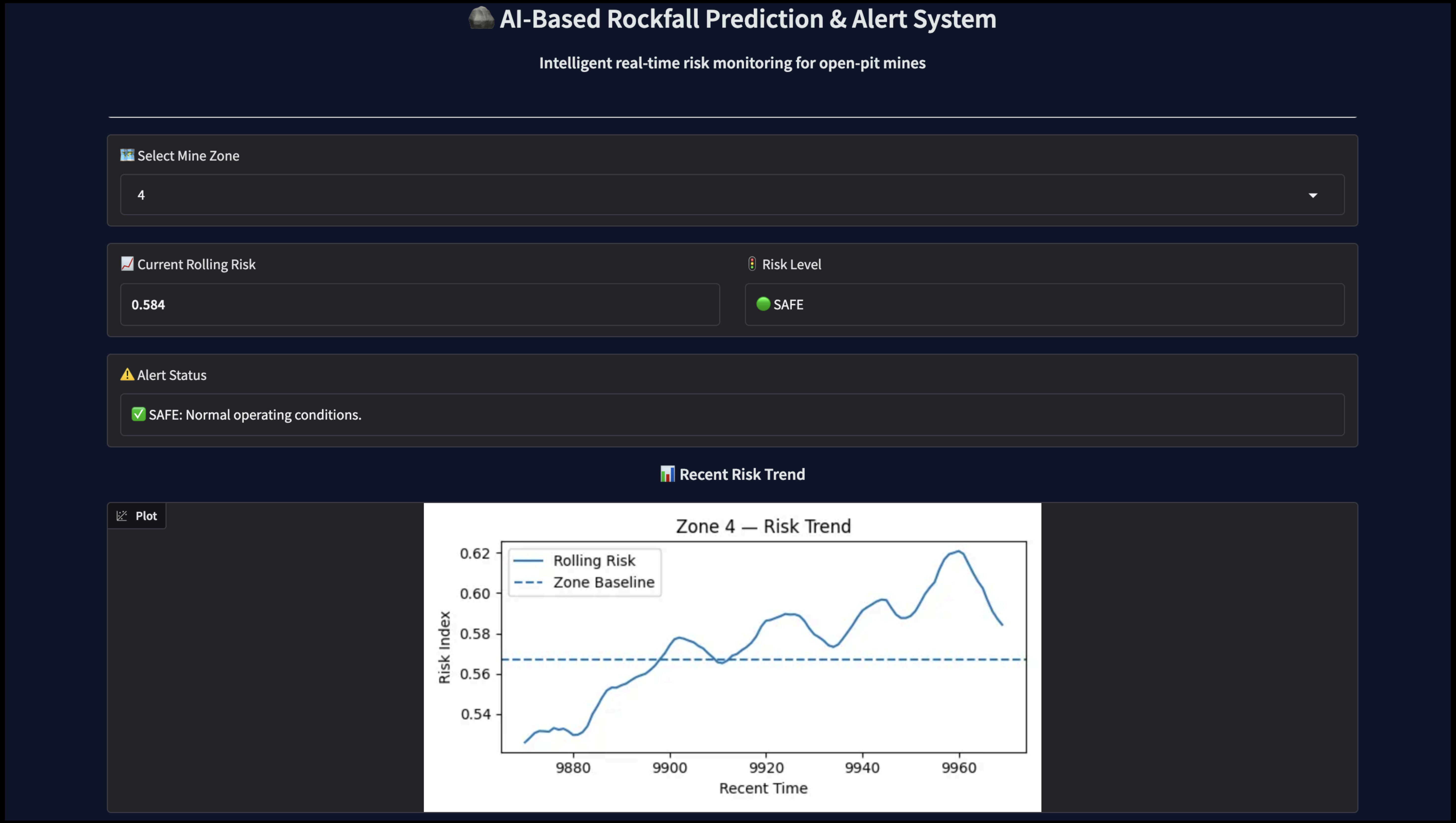
SYSTEM DEPLOYMENT & DASHBOARD DEMONSTRATION

SYSTEM DEPLOYMENT

- END-TO-END PIPELINE DEPLOYED AS AN INTERACTIVE MONITORING SYSTEM
- MODEL INFERENCE EXECUTED IN REAL TIME ON INCOMING TEMPORAL DATA
- RISK SCORES, TRENDS, AND ALERTS UPDATED DYNAMICALLY PER MINE ZONE

DASHBOARD FUNCTIONALITIES

- ZONE-WISE RISK VISUALIZATION AND TREND ANALYSIS
- DYNAMIC RISK STATUS: SAFE / WATCH / ALERT
- PERSISTENT ALERT LOGIC TO REDUCE FALSE ALARMS
- INTERACTIVE SELECTION OF MINE ZONES FOR MONITORING



INTERACTIVE DASHBOARD FOR REAL-TIME MINE RISK MONITORING

DEMONSTRATES PRACTICAL DEPLOYABILITY OF THE PROPOSED AI-BASED RISK PREDICTION FRAMEWORK.

KEY CONTRIBUTIONS & IMPACT

KEY CONTRIBUTIONS

1. REALISTIC TEMPORAL RISK DATASET
- DESIGNED A LARGE-SCALE SYNTHETIC DATASET SIMULATING DYNAMIC OPEN-PIT MINE BEHAVIOR
- CAPTURES MULTI-SENSOR INTERACTIONS AND ZONE-SPECIFIC INSTABILITY PATTERNS

2. TEMPORAL DEEP LEARNING FRAMEWORK
- PROPOSED AN LSTM-BASED MODEL FOR CONTINUOUS ROCKFALL RISK PREDICTION
- EFFECTIVELY CAPTURES LONG-TERM TEMPORAL DEPENDENCIES IGNORED BY STATIC MODELS

3. DYNAMIC RISK SCORING & ALERTING LOGIC
- DEVELOPED ROLLING RISK ANALYSIS WITH TREND-AWARE ALERT GENERATION
- INTRODUCED PERSISTENCE-BASED ALERTS TO REDUCE FALSE POSITIVES

4. END-TO-END DEPLOYABLE SYSTEM
- INTEGRATED PREDICTION, RISK SCORING, ALERTS, AND VISUALIZATION
- DEMONSTRATED REAL-TIME DECISION SUPPORT THROUGH AN INTERACTIVE DASHBOARD

IMPACT

- ENHANCES PROACTIVE SAFETY MONITORING IN OPEN-PIT MINING OPERATIONS
- ENABLES EARLY DETECTION OF GRADUAL SLOPE INSTABILITY
- REDUCES DEPENDENCE ON MANUAL INSPECTION AND STATIC THRESHOLDS
- BRIDGES THE GAP BETWEEN ACADEMIC MODELS AND REAL-WORLD DEPLOYMENT

LIMITATIONS & FUTURE WORK

LIMITATIONS

1. SYNTHETIC DATASET DEPENDENCY
   - CURRENT EVALUATION IS BASED ON REALISTICALLY SIMULATED DATA
   - REAL-WORLD MINE SENSOR DATA WAS NOT AVAILABLE FOR VALIDATION\

2. SINGLE-MODEL ARCHITECTURE
   - THE FRAMEWORK FOCUSES ON LSTM-BASED TEMPORAL MODELING
   - TRANSFORMER-BASED OR HYBRID ARCHITECTURES WERE NOT EXPLORED

3. ZONE-LEVEL RISK MODELING
   - RISK PREDICTIONS ARE PERFORMED AT THE ZONE LEVEL
   - FINE-GRAINED SPATIAL MODELING AT BENCH OR PIXEL LEVEL IS NOT INCLUDED

FUTURE WORK

1. INTEGRATION WITH REAL MINE SENSOR DATA
   - VALIDATE AND ADAPT THE SYSTEM USING LIVE IOT AND GEOTECHNICAL DATA

2. ADVANCED TEMPORAL MODELS
   - EXTEND THE FRAMEWORK USING TRANSFORMERS OR ATTENTION-BASED NETWORKS
   - IMPROVE LONG-RANGE DEPENDENCY MODELING

3. SPATIAL–TEMPORAL RISK MAPPING
   - INCORPORATE SPATIAL GRAPH OR VISION-BASED MODELS FOR SLOPE-WIDE ANALYSIS

4. AUTOMATED RESPONSE SYSTEMS
   - INTEGRATE ALERTS WITH EVACUATION PLANNING AND AUTONOMOUS MONITORING DRONES

CONCLUSION & KEY TAKEAWAYS

CONCLUSION

- PRESENTED AN AI-DRIVEN ROCKFALL RISK PREDICTION AND ALERT SYSTEM FOR OPEN-PIT MINES
- PROPOSED A TEMPORAL DEEP LEARNING FRAMEWORK (LSTM) TO MODEL RISK EVOLUTION OVER TIME
- INTEGRATED PREDICTION, RISK SCORING, ALERTING, AND VISUALIZATION INTO A UNIFIED SYSTEM

KEY TAKEAWAYS

- TEMPORAL MODELING SIGNIFICANTLY OUTPERFORMS STATIC ML BASELINES
- CONTINUOUS RISK INDICES ENABLE EARLY DETECTION OF GRADUAL SLOPE INSTABILITY
- PERSISTENT ALERT LOGIC REDUCES FALSE ALARMS AND IMPROVES TRUSTWORTHINESS
- THE SYSTEM IS PRACTICAL, SCALABLE, AND DEPLOYABLE FOR REAL-WORLD MINE SAFETY

IMPACT

- ENHANCES DECISION-MAKING SPEED AND ACCURACY FOR MINE OPERATORS
- IMPROVES WORKER SAFETY THROUGH PROACTIVE RISK AWARENESS
- ESTABLISHES A STRONG FOUNDATION FOR INTELLIGENT MINE MONITORING SYSTEMS

THANK YOU!