Machine-Learning-Based Intelligent Safety Risk Early Warning for Live-Line Work in Distribution Networks

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ABSTRACT Live-line work reduces scheduled outages and improves distribution reliability, but it also places workers in a changing environment where energized parts, tool condition, human behavior, weather, and work-space constraints interact. Conventional controls based on work-ticket review, manual supervision, and fixed thresholds are effective for explicit prohibitions but are less capable of recognizing a gradual rise in risk. This study develops a multisource data system covering work plans, personnel qualifications, tool tests, grid status, environmental sensing, video events, and historical incidents. It proposes an early-warning framework that combines rule constraints, machine-learning estimation, probability calibration, graded response, and feedback-based updating. XGBoost is used for structured records, while temporal and visual modules capture state trends and unsafe behavior. Their calibrated outputs are fused with mandatory rules rather than allowed to override them. Cost-sensitive learning, task-and-time-grouped validation, calibration analysis, and interpretable evidence are included to address rare hazardous events, leakage, false alarms, and opaque decisions. A four-level response process, human confirmation, drift monitoring, and model audit are then specified. The framework is intended to support earlier intervention while retaining the authority of safety codes and the decision responsibility of on-site personnel.

INDEX TERMS Distribution network; Live-line work; Machine learning; Risk early warning

I. INTRODUCTION

A. RESEARCH BACKGROUND

Distribution networks connect the power system directly to end users. Their equipment is numerous, geographically dispersed, and exposed to traffic, vegetation, weather, and public activity. As data centers, rail transit, hospitals, and continuous-process factories demand higher supply reliability, the conventional assumption that maintenance must always require an outage becomes increasingly difficult to sustain. Live-line methods use insulated sticks, rubber-glove techniques, aerial devices, and bypass systems to remove defects, make connections, transfer load, and replace components while the circuit remains energized. The Chinese technical guide for live working on distribution lines defines operating methods, minimum approach requirements, personnel conditions, and tool requirements [1].

Keeping the feeder energized does not remove risk. It replaces some of the protection created by electrical isolation with stricter demands on skill, insulation, work organization, and real-time control. Electric shock, arc exposure, induced voltage, falls, mechanical injury, and road interference may occur in the same task. Line configuration, loading, humidity, wind, visibility, and contamination can alter the margin available to the crew. The national safety code therefore requires work authorization, site survey, supervision, live-work precautions, and clear suspension conditions [2]. These provisions establish the safety floor, but a single assessment before work cannot always show whether risk is rising during a changing operation.

Many utilities already hold work tickets, qualification files, tool-test records, weather feeds, vehicle locations, video, and violation histories. The difficulty is that these records sit in separate systems and use different clocks and identifiers. A supervisor still has to assemble the picture from experience. A wind reading may remain below its stop-work limit while a moving boom, long duty time, and a complicated crossing jointly reduce the available margin. Machine learning can help rank such combinations, but it must remain subordinate to technical rules, professional judgment, and on-site confirmation.

B. PROBLEM STATEMENT

Safety warning for live-line work is not an ordinary binary classification problem. Serious accidents and forced suspensions are rare, so hazardous examples are greatly outnumbered by normal windows. Records from the same crew, feeder, or work ticket are also strongly related over time; random train-test splitting can allow a model to memorize an object rather than learn a risk pattern. In addition, qualifications and work type change slowly, whereas posture, weather, distance, and behavior change during the task. False alarms interrupt work and exhaust attention, but a missed warning may have unacceptable consequences. Gu and Zhang likewise identify management, personnel, equipment, and environmental conditions as coupled sources of live-work risk [3].

A conventional risk matrix remains transparent and easy to audit, yet its categories are coarse and often depend on subjective scoring. A purely data-driven model offers finer ranking but may reproduce historical weaknesses or fail under a new work method, extreme weather, or unfamiliar equipment. This study therefore uses two tracks. Explicit prohibitions and mandatory suspension conditions are handled by a rule engine. Cases that remain within the permitted range but contain several weak signals are evaluated by machine learning and then reviewed by responsible personnel.

C. RESEARCH DESIGN AND CONTRIBUTION

The contribution is methodological rather than a claim of unreported field accuracy. First, work-ticket, sensor, and video events are placed on a common task timeline. Second, mandatory rules and predictive scores remain separate pieces of evidence, so a model cannot soften a prohibition. Third, evaluation includes high-risk recall, false alarms per work hour, warning lead time, and calibration instead of relying on overall accuracy. These choices connect model development to the decisions that crews actually need to make.

TABLE 1. Core Risk Domains

Domain	Typical Feature	Data Source
Task	Work type	Work ticket
Person	Skill level	Staff file
Tool	Test status	Tool ledger
Grid	Load state	SCADA
Weather	Wind and rain	Weather API
Space	Safety distance	Video/LiDAR
Behavior	Rule deviation	Video event
History	Near miss	Event record
Control	Response status	Warning log

II. THEORETICAL BASIS AND RISK FORMATION

A. SAFETY CONSTRAINTS OF LIVE-LINE WORK

Work steps also depend on one another. An incomplete survey affects the work plan; insufficient covering increases the exposure of later actions; a change in boom position alters the worker-to-conductor distance. The same movement can be manageable with stable weather and full covering but unacceptable after wind rises or communication is lost.

Treating each video frame or sensor reading as an independent sample would erase this accumulation. The useful unit of analysis is a work task observed within a particular step and time window[4-5].

B. COUPLED FACTORS AND RISK EVOLUTION

Field risk rarely begins with one isolated threshold. A crew normally considers the possible harm from the energized component, the actual worker position, the continuity of insulation, and whether supervision can keep pace with the work[6]. Higher humidity, for example, does not necessarily stop a task. The assessment changes when contaminated insulation, compressed clearance, and difficult access appear at the same time. The model therefore observes hazards, exposure, protective condition, and management control together without reducing them to a simple sum[7].

This study separates baseline, triggering, and corrective components. Work type, line structure, experience, and historical events determine a prior condition. Weather, equipment status, spatial distance, and behavior update that condition during work. Added covering, a changed position, tool replacement, or suspension then modifies it again. With baseline features x_b, dynamic features x_t, and current controls c_t, the warning probability is expressed as

$$P_t = P(y_t \mid x_b, x_t, c_t).$$

Including c_t prevents an alarm from continuing after the crew has removed its cause.

C. SCOPE OF MACHINE-LEARNING ASSISTANCE

Machine learning is useful when interactions are too numerous to enumerate as fixed rules. Chang et al. combined HOG features and a support vector machine to detect personnel and entry into dangerous areas at power-work sites, reporting 92% accuracy in their experiment [8]. Visual evidence can therefore support supervision, but helmets, workers, and boundary lines represent only part of live-work risk. Occlusion, glare, rain, fog, and camera angle may all reduce confidence. A practical warning system combines video with task and sensor information and asks for review when confidence is low.

Coverage of the training data defines the model boundary. Samples from aerial-device work in one region do not automatically represent bypass work, cable equipment, or another climate. Before deployment, the supported voltage levels, work types, devices, locations, and weather ranges must be documented. An input outside that domain should be marked uncertain rather than assigned an apparently precise low-risk score.

III. WARNING REQUIREMENTS AND MULTISOURCE DATA

A. WORKFLOW AND WARNING POINTS

Tang et al. applied artificial intelligence to identifying high-risk areas in non-outage distribution work through spatial association and multimodal features [9]. Such spatial analysis can reveal entry into a hazardous area or a tool approaching an energized part, but it cannot distinguish a planned movement from an abnormal one without the ticket and the current step. In this framework, task ID and a synchronized time line join these sources; alerts from different systems are not merely stacked.

Lead time is measured from the point at which the system first supplies actionable evidence, not from the moment a limit has already been exceeded. A rising wind trend combined with increased boom movement can offer time for an orderly withdrawal. The record therefore distinguishes detection time, warning time, human confirmation, and completion of the response.

B. FEATURE SYSTEM AND TIME ALIGNMENT

Liu used environment, weather, and equipment status in a data-driven assessment of non-outage distribution work [10]. The main feature groups are summarized in Table 2.

The first practical problem after connection is usually inconsistent time. A ticket is recorded by step, weather updates by the minute, location and posture arrive several times per second, and video is frame based. This study uses the start and end of each step as the outer boundary and constructs 30- or 60-second observation windows inside it. Minimum distance is retained for clearance variables, whereas wind and boom posture retain both level and rate of change. Short actions use a shorter window; a single fixed duration is not imposed on every method.

TABLE 2. Feature Schema

Group	Static	Dynamic	Source	Rate	Use
Task	Work type	Step state	Ticket	Per step	Prior
Staff	Skill	Workload	Staff DB	Minute	Exposure
Tool	Test date	Sensor value	Tool DB	Second	Barrier
Grid	Topology	Load	SCADA	Second	Severity
Site	Layout	Distance	Video	Frame	Trigger

C. LABELS AND DATA QUALITY

Labels determine what the model learns. Accidents alone are too rare and omit dangerous states that were stopped in time. The proposed scheme also uses near misses, red-line violations, suspensions, manually escalated warnings, and ordinary anomalies. Safety specialists review the label rule and identify event start, peak, and clearance. A window may carry a risk level, risk type, and intervention requirement, allowing both classification and multi-task analysis.

Information generated after intervention must not leak into the prediction. A "job suspended" field cannot be used to forecast the condition that caused suspension, and a manual warning entered after the event cannot appear in an earlier feature window. Every derived feature is therefore assigned an availability time. Table 3 lists the principal label and quality controls.

TABLE 3. Label and Quality Controls

Issue	Risk	Control	Owner	Record	Check
Rare event	Low recall	Cost weight	Modeler	Class log	PR-AUC
Missing data	False calm	Missing flag	Data team	Gap log	Coverage
Label drift	Wrong target	Expert review	Safety team	Label note	Agreement
Data leak	High bias	Time cutoff	Auditor	Feature time	Back test
Site bias	Weak transfer	Site split	Operator	Site code	External test

IV. MACHINE-LEARNING WARNING MODEL

A. RULE AND LEARNING CHANNELS

A transparent logistic model is built first, followed by random forest, support vector machine, and gradient boosting. Random forest reduces the variance of a single tree and handles mixed, nonlinear features [11]. Support vector machines can perform well with moderate samples and high-dimensional features, but their probability output and scaling require additional work [12]. The baseline models also expose leakage: an implausibly easy prediction often indicates that the data contain information from after the event.

Rule hits are not copied into the ordinary feature set. They remain independent evidence in the fusion stage. Samples that do not hit a rule but are later confirmed as hazardous receive special review because they may reveal a combination that existing rules do not express. Rule and model versions are controlled separately, and a revised standard triggers an impact assessment.

B. STRUCTURED MODEL AND CLASS IMBALANCE

Work tickets, personnel files, tool records, weather summaries, and online statistics are mainly tabular, with categorical values, continuous measurements, and missing fields. XGBoost is selected as the principal structured model and logistic regression is retained as a comparison. XGBoost successively corrects examples that earlier trees explain poorly and uses regularization to limit complexity [13]. Training first defines the consequence of missing a high-risk case, C_{FN}, and then adjusts the false-alarm cost, C_{FP}, to the review capacity of a crew. A higher offline recall is not useful when it produces repeated warnings that cannot be checked.

SMOTE creates minority examples by interpolation between neighboring records [14], but indiscriminate use can violate physical or categorical constraints. Qualification level and work method are not linearly interpolated; wind, humidity, and distance remain within feasible ranges. Cost weighting is therefore the primary treatment, while synthetic sampling is an explicitly tested alternative.

C. TEMPORAL AND VISUAL MODELING

Dynamic risk depends on change over time rather than one isolated value. LSTM retains longer dependencies through its gated state and is suitable for wind, posture, distance, and physiological sequences [15]. The input consists of the previous k windows, and the output estimates whether the next window enters a hazardous state. First differences, trend slopes, and exceedance duration are included so that the network does not rely only on absolute level. Irregular signals are resampled according to safety meaning, with the interval retained as a feature.

The visual component does not pass entire video streams to the fusion model. Edge devices first detect workers, aerial equipment, tools, and defined areas, then produce a per-second event record containing head count, minimum distance, occlusion, and action category. Missing protective equipment requires confirmation across several frames, while action order needs a longer clip. A single frame is too sensitive to turning posture and reflected light. Complete occlusion is marked unavailable rather than interpreted as an absence of violations.

Late fusion uses calibrated probabilities from the structured, temporal, and visual modules. With p_s, p_t, and p_v as their outputs and r as the rule level, the combined score is

$$R = \max(r, w_s p_s + w_t p_t + w_v p_v)\,.$$

Weights are estimated by scenario. When a modality is missing or unreliable, its weight falls and the interface reports lower confidence instead of replacing it with zero.

D. CALIBRATION AND EXPLANATION

A displayed score of 0.8 is easily mistaken for an 80% chance of an event, although a raw classifier score has no such guarantee. A separate calibration set is therefore retained. Platt scaling and isotonic regression are compared for tree models, while temperature scaling is used for the temporal network. The selected method must make cases with similar scores show similar observed frequencies. Guo et al. demonstrate that correct classification does not necessarily imply reliable confidence [16]. Brier score and expected calibration error are consequently reported with recall.

Explanation is adapted to its user. The crew receives a short statement such as "wind variability increased while minimum clearance decreased." Safety analysts can view the time curve, feature contribution, and comparable events. SHAP provides a consistent local contribution estimate for structured predictions [17]. It is not treated as causal proof, but it helps identify faulty data, unstable features, and conditions that personnel can change.

TABLE 4. Model Modules

Module	Input	Output
Rule engine	Safety rules	Hard limit
XGBoost	Tabular data	Base risk
LSTM	Time series	Trend risk
Vision	Video events	Behavior risk
Calibrator	Raw scores	Probability
Fusion	All scores	Risk level
Explainer	Feature values	Risk reason

V. WARNING SYSTEM AND CLOSED-LOOP RESPONSE

A. SYSTEM ARCHITECTURE AND ONLINE INFERENCE

The system contains data access, feature service, model service, warning center, and feedback governance. Task ID links tickets, personnel, tools, SCADA, weather, position, and video events. The feature service computes the same variables in training and production. Visual detection runs at the edge where latency matters; structured and temporal fusion runs centrally. The warning center manages levels, delivery, and confirmation, while the governance service stores responses, false alarms, missed events, and model versions. This design follows the continuing cycle of identification, analysis, treatment, monitoring, and communication emphasized by ISO 31000 [18].

Online inference requires a degraded mode. During a network outage, edge equipment can continue basic distance and behavior rules and transmit the record later. If the central model is unavailable, the crew continues under the work ticket and safety code; loss of an intelligent service must not remove basic control. Data delay, missing rate, inference latency, and service status are monitored so that "no data" is never displayed as "low risk."

A field alert needs more than a color and score. It identifies the task, time, evidence, responsible reviewer, and an appropriate action, for example: "boom movement increased and the 30-second minimum clearance fell; supervisor review required." Repeated yellow alerts from the same cause enter a cooldown period while values continue to update. Red warnings are never silenced. A warning closes only after the condition remains normal for a complete window and a responsible person confirms that the measure has taken effect.

B. WARNING LEVELS AND RESPONSES

The four levels are not equal probability intervals. Blue is recorded for observation without interrupting work. Yellow indicates a rising trend or reduced data quality and requires a supervisor to inspect the situation. Orange pauses the current step while the person in charge checks the method and protection. Red is reserved for prohibited conditions, violated clearance, or another event requiring immediate action. A low-probability event with severe rule consequences still becomes red, while an uncertain video anomaly may begin as yellow. The routine response states are shown in Table 5.

TABLE 5. Routine Warning Response

Level	Trigger	Action	Owner
Blue	Normal range	Observe	Operator
Yellow	Trend rise	Recheck	Supervisor

Orange response is led by the person in charge and includes suspension, method review, and additional protection. Red response stops the relevant operation and initiates the prescribed escalation. Thresholds are chosen from response capacity rather than model convenience. If a crew can review one yellow alert per hour, a threshold producing five alerts is unusable. Red recall is set first; among thresholds meeting it, the one with the lower review burden is preferred.

C. HUMAN CONFIRMATION AND CLOSURE

The responsibility chain covers model generation, field confirmation, action, recheck, and closure. Blue information is viewed by the operator, yellow by the supervisor, orange by the person in charge, and red is also sent to safety management. Confirmation records one of four states: accepted, false alarm, insufficient information, or resolved. A short reason is required so that the record can later support audit and labeling.

Human review is not an unrestricted override. When a warning is rejected, the reviewer identifies occlusion, positioning error, task change, or another cause, and the original evidence remains available. Conversely, one rejection does not immediately turn the sample into a safe training label. Periodic expert review prevents operational pressure from teaching the model to ignore genuine risk.

VI. VALIDATION, DEPLOYMENT, AND GOVERNANCE

A. VALIDATION DESIGN AND METRICS

Data are grouped by work task and divided chronologically into training, calibration, and test sets. Windows from one ticket never appear in different sets, because neighboring windows share too much information. Earlier periods are used for training, later periods for testing, and an unseen region or crew provides an external test. Changes in equipment or procedures are marked so that concept drift can be distinguished from ordinary error.

Comparisons include a rule matrix, logistic regression, random forest, support vector machine, and XGBoost. LSTM and visual events are added only when continuous data are sufficient. Ablation removes personnel, tool, weather, temporal, and visual groups in turn. Sculley et al. note that hidden technical debt in machine-learning systems often arises from data dependencies, feedback loops, and undeclared coupling [19]; the validation record therefore includes feature sources, versions, and service dependencies.

Because most windows are safe, overall accuracy can look strong while hazardous cases are missed. Evaluation begins with high-risk recall and false alarms per work hour. F2 and PR-AUC compare models, warning lead time shows whether action is possible, and Brier score with expected calibration error evaluates probability quality. Results are also separated by work method, region, and weather. Table 6 summarizes the evaluation and governance measures.

TABLE 6. Validation and Governance

Goal	Metric	Control
High-risk find	Recall/F2	Cost weight
Alert burden	False alarms	Threshold
Early action	Lead time	Trend model
Probability fit	Brier/ECE	Calibration
Site transfer	External test	Site split
Model stability	Drift score	Retraining
Traceability	Version log	Audit trail

After offline testing, the model enters shadow operation. It records predictions without issuing controlling alerts, allowing managers to compare them with actual decisions and check alert volume, explanation, and latency. Yellow prompts are then piloted on standardized tasks before orange linkage is considered. Red rule control requires professional review and emergency exercises and is not delegated directly to an experimental model.

B. DRIFT, SECURITY, AND AUDIT

Work methods, personnel, equipment, and acquisition systems change after deployment. The service monitors feature distributions, missing rates, predicted probabilities, alert proportions, and confirmed outcomes. A shifted input with stable outcomes may require a preprocessing update; a changed relation between inputs and labels requires retraining and external validation. A scheduled job never replaces the production model automatically. Every release passes replay testing, review, and rollback preparation.

The NIST AI Risk Management Framework organizes governance around govern, map, measure, and manage functions [20]. In this setting, data, algorithm, business approval, and field-use responsibilities are assigned separately. Training scope, feature list, parameters, thresholds, and test reports are retained. Access control and integrity checks protect against poisoned inputs, unauthorized interfaces, video leakage, and forged warnings. Production accepts signed model versions, and temporary changes remain auditable.

C. PHASED DEPLOYMENT AND LIMITATIONS

Deployment proceeds in four stages. The first standardizes task codes, timestamps, and basic ledgers. The second implements the rule engine and data-quality monitoring. The third trains a structured model for work types with sufficient historical records and runs it in shadow mode. Temporal and visual modules are introduced only in the fourth stage. Beginning with a complex multimodal model while the basic data remain unstable usually produces a demonstration that cannot be maintained.

Cross-utility transfer must account for different meanings behind similar field names. "Step start" may refer to different operational moments, and camera position changes the geometry of distance estimates. Feature definitions, evaluation scripts, and model architecture can be shared, while raw video and personnel information remain local. Parameter transfer or federated learning may reduce data movement, but probability calibration and external validation are still repeated with local samples.

A limitation must be stated directly: no enterprise-scale continuous dataset is publicly available for independent replication. The proposed windows, fusion weights, and warning levels are therefore a design framework rather than universal parameters. Climate, network structure, and work practice can produce different alert volumes under the same threshold. Future work should construct a de-identified multi-region benchmark, measure the incremental value of structured, temporal, and visual data, and estimate uncertainty for extreme weather and new work methods.

VII. CONCLUSION

This study began with a field problem: work tickets and manual supervision protect explicit boundaries but do not always reveal that several weak signals are deteriorating together. It aligns tickets, personnel and tool records, weather, positioning, and video events by work step. Mandatory conditions remain in the rule base, while XGBoost, temporal modeling, and visual events rank the uncertain cases. Their outputs are calibrated and presented with evidence time and principal causes for human review.

Practical value depends on finding genuine high-risk states early without overwhelming crews with repeated alerts. Validation is therefore grouped by task and time and includes false-alarm rate, lead time, and calibration error. Deployment starts with data alignment and shadow operation before yellow and orange linkage is introduced; red response remains governed by safety rules and the person in charge. Because continuous public field data are unavailable, no universal accuracy is claimed. Further work should quantify the contribution of each modality on de-identified operational records and examine transfer and lightweight edge inference.

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