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Machine Learning Approaches for Detecting Land Ownership Disputes Through Historical Survey Record Analysis

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Abstract: Secure land ownership forms the foundation of economic development, investment confidence, social stability, and effective land governance. However, historical inconsistencies in cadastral surveys, paper-based land records, boundary re-surveys, inheritance claims, and administrative documentation continue to generate ownership disputes that delay property transactions, increase litigation, and weaken public confidence in land administration systems. As land information repositories become increasingly digitised, substantial opportunities have emerged to transform decades of archived survey records into predictive intelligence for dispute prevention rather than post-conflict resolution. This study investigates the application of machine learning techniques for detecting potential land ownership disputes through the systematic analysis of historical survey records, cadastral maps, title registrations, boundary adjustment documents, and geospatial parcel histories. The proposed analytical framework integrates natural language processing for legal document interpretation, graph-based relationship modelling for ownership lineage reconstruction, anomaly detection for identifying conflicting survey records, and supervised classification algorithms for dispute risk prediction. Feature engineering incorporates temporal ownership transitions, parcel geometry inconsistencies, surveyor records, registration frequency, and historical boundary modifications to improve predictive accuracy. Explainable artificial intelligence is further employed to enhance transparency by identifying the factors contributing to each dispute prediction, thereby supporting legal defensibility and stakeholder trust. The study demonstrates that machine learning can transform historical cadastral archives into proactive decision-support systems that strengthen land administration, reduce litigation, accelerate property transactions, and improve tenure security through evidence-based dispute prevention.

Keywords: Machine Learning; Land Ownership Disputes; Historical Survey Records; Cadastral Analytics; Explainable Artificial Intelligence; Land Administration

1. INTRODUCTION

1.1 Land Ownership Disputes as Evidence-Consistency Problems

Land ownership disputes are increasingly recognised as evidence-consistency problems arising from contradictions among legal, spatial, temporal, and administrative records rather than merely disagreements over physical boundaries [1]. A single parcel may become the subject of competing title claims when different documentary sources assign ownership rights to separate individuals or institutions without a clear legal reconciliation process [2]. Overlapping survey plans, duplicate parcel registrations, and inconsistent cadastral records further complicate ownership determination by introducing conflicting spatial representations of the same landholding [3]. Inheritance-related ownership fragmentation frequently divides property among multiple beneficiaries, while unrecorded transfers create discontinuities within documented ownership histories that obscure legitimate title succession [4]. Boundary displacement resulting from inaccurate resurveys, natural landscape change, or informal occupation may progressively separate legal parcel descriptions from their physical locations on the ground [5]. Fraudulent alterations to survey plans, title documents, and cadastral records further undermine the integrity of land administration by introducing intentionally misleading evidence capable of supporting unlawful ownership claims [1]. Additional complexity arises where customary land tenure systems coexist with statutory registration frameworks, creating conflicting legal interpretations of ownership rights over the same parcel [3]. Because these ownership disputes emerge from multiple interacting inconsistencies distributed across documentary and spatial evidence, examining a title deed or survey plan in isolation rarely reveals the complete legal and historical evolution of a parcel [6].

1.2 Why Historical Survey Records Matter

Historical survey records constitute an essential source of evidence because they preserve the chronological development of land parcels from their original survey through successive ownership and administrative changes [7]. Archived survey plans record original parcel dimensions, survey coordinates, bearings, and boundary descriptions that provide authoritative references for reconstructing historical parcel geometry and legal extent [8]. These records also preserve ownership succession through successive registrations, transfers, inheritance transactions, and other legally recognised changes affecting property rights over time [9]. Boundary adjustments resulting from resurveys, road construction, subdivision, consolidation, or government acquisition are likewise documented within historical survey archives, allowing investigators to reconstruct parcel evolution across multiple decades [2]. Surveyor certifications, registration dates, official approvals, and neighbouring parcel relationships further strengthen evidential continuity by linking individual survey documents with broader cadastral records and surrounding landholdings [8]. The principal value of historical survey records therefore lies not only in the information contained within individual documents but also in the continuous temporal evidence they collectively provide regarding parcel development and ownership history [5]. However, these archives frequently exist in fragmented, paper-based, inconsistent, and heterogeneous formats that vary considerably in accuracy, completeness, terminology, and spatial representation, making manual reconciliation across thousands of records extremely difficult and time-consuming [1]. Consequently, computational methods capable of identifying recurring patterns of contradiction offer a practical means of supporting modern land administration and dispute investigation [7].

1.3 Research Gap, Aim and Contributions

Despite substantial progress in cadastral digitisation and electronic land administration, many contemporary systems continue to function primarily as digital repositories rather than intelligent analytical platforms capable of reconstructing historical ownership evidence and identifying inconsistencies across multiple records [8]. Existing land information systems often maintain only weak connections between historical survey documents and current parcel records, limiting their ability to reconstruct complete ownership chains or identify undocumented changes occurring throughout a parcel's legal history [4]. Automated detection of ownership-chain breaks, duplicate registrations, conflicting survey information, and documentary inconsistencies remains relatively limited despite increasing volumes of digitised cadastral information [1]. Furthermore, textual legal documents, survey plans, cadastral maps, and spatial boundary information are frequently analysed independently rather than being integrated into unified evidence frameworks capable of supporting comprehensive ownership verification [6]. Although machine-learning techniques have demonstrated considerable success in spatial prediction and document analysis, relatively few studies provide explainable outputs suitable for legal decision-making, where transparency, traceability, and evidential justification are essential requirements [9].

This study therefore aims to develop a machine-learning framework that reconstructs historical parcel evidence and assigns dispute-risk probabilities to individual landholdings by integrating documentary, spatial, and temporal information [3]. The proposed framework contributes through historical survey-record harmonisation, parcel lineage reconstruction, spatial and documentary anomaly detection, multi-model dispute classification, and explainable, legally traceable risk reporting capable of supporting evidence-based land administration, dispute resolution, and cadastral governance [5].

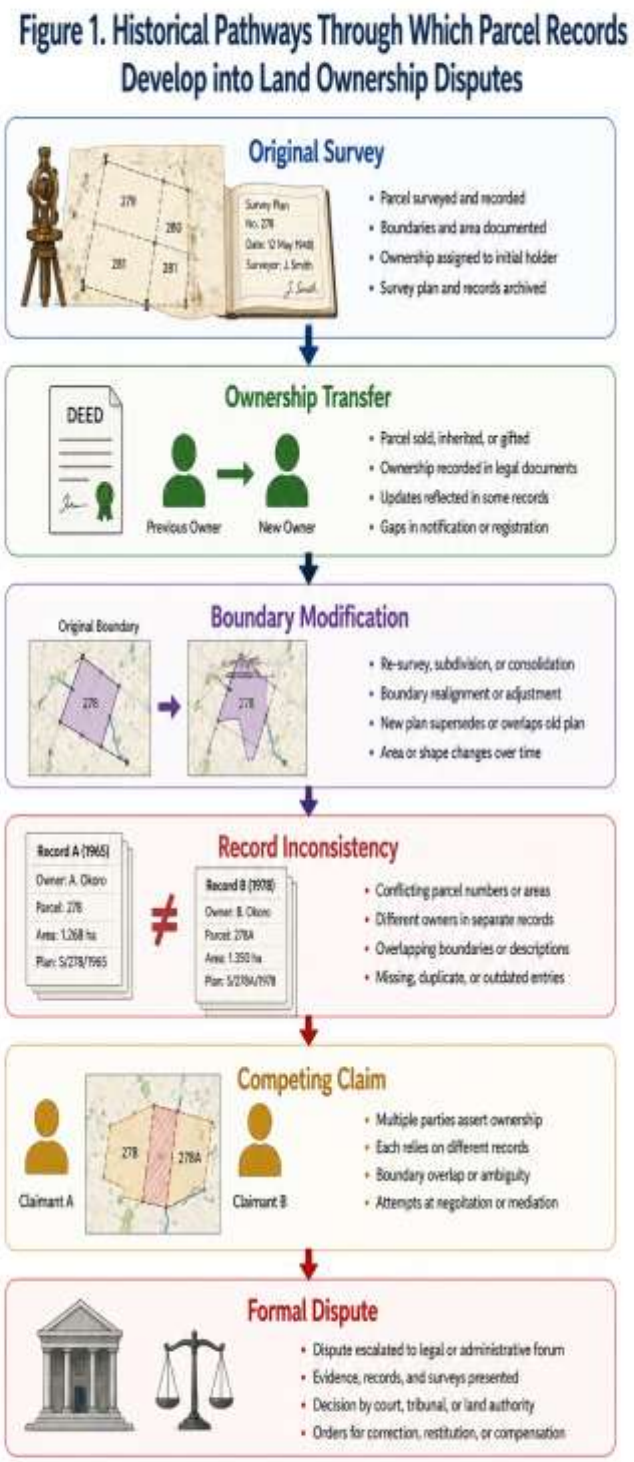

Figure 1. Historical Pathways Through Which Parcel Records Develop into Land Ownership Disputes

2. ANATOMY OF HISTORICAL SURVEY RECORDS AND OWNERSHIP CONFLICTS

2.1 Structure and Evidential Content of Survey Archives

Historical survey archives constitute the evidential foundation of land administration because they preserve legal, spatial, and administrative records describing the origin, evolution, and ownership of individual land parcels across successive generations [11]. Survey plans provide detailed representations of parcel boundaries, dimensions, bearings, coordinates, and monument locations established during official cadastral surveys, while cadastral maps illustrate the spatial relationships among neighbouring parcels, transportation corridors, public land, and administrative boundaries [7]. Field books complement survey plans by recording original field observations, measurement procedures, reference points, and survey computations undertaken during boundary demarcation [14]. Coordinate registers preserve geodetic coordinates and control-point information that support the reconstruction and verification of historical parcel geometry under recognised surveying standards [9]. Legal ownership is documented through deeds, conveyances, mutation records, probate documents, planning approvals, court judgments, and tax or valuation records, each providing evidence of ownership transfer, inheritance, subdivision, acquisition, compensation, or legal determination affecting parcel rights over time [12].

The evidential content contained within survey archives exists in multiple information formats requiring different methods of interpretation and analysis [6]. Structured data include coordinate registers, parcel identifiers, registration numbers, and valuation databases organised within predefined formats suitable for computational processing [13]. Semi-structured records comprise mutation forms, planning approvals, and administrative registers containing partially standardised information [8]. Textual documents such as deeds, probate records, and court judgments provide narrative legal evidence, whereas cartographic records including survey plans and cadastral maps preserve spatial representations of parcel boundaries [10]. Handwritten field books, annotations, signatures, and historical marginal notes introduce additional evidential value but present substantial challenges for automated interpretation because of inconsistent writing styles and document deterioration [7].

2.2 Typology of Record-Based Ownership Disputes

Historical land ownership disputes arise through multiple forms of documentary and spatial inconsistency, each producing distinctive evidence patterns that require specialised analytical approaches for reliable detection [8]. Boundary-overlap disputes occur when neighbouring parcels occupy overlapping geographic space because of conflicting survey plans, inaccurate boundary definition, or inconsistent cadastral updates [13]. Duplicate-title disputes arise where multiple legal ownership documents are issued for the same parcel, creating competing ownership claims supported by apparently valid documentary evidence [10]. Ownership-chain discontinuities develop when transfers, inheritance events, or conveyances remain undocumented, preventing the reconstruction of continuous legal ownership histories and creating uncertainty regarding legitimate title succession [6]. Parcel identity mismatches occur when inconsistent parcel identifiers, numbering systems, or administrative references prevent reliable linkage between historical and contemporary cadastral records [14]. Illegal subdivision disputes arise where parcels are divided without statutory approval, producing discrepancies between registered land records and actual land occupation [9].

Encroachment-related claims emerge when buildings, fences, roads, or agricultural activities extend beyond legally recognised parcel boundaries, often generating conflict between neighbouring landowners [11]. Survey coordinate conflicts develop when successive surveys produce inconsistent coordinates, bearings, or boundary monuments because of differing surveying methods, coordinate reference systems, or measurement accuracy [7]. Competing inheritance claims frequently result from disputed wills, customary succession practices, or conflicting probate documentation that assign ownership rights to multiple beneficiaries [12]. Registration-priority disputes occur where competing transactions are submitted within similar time periods, creating uncertainty regarding the legal precedence of ownership registration [8]. Because each dispute category produces distinct documentary, spatial, and temporal characteristics, effective machine-learning models require tailored feature-engineering strategies capable of extracting evidence specific to each ownership conflict rather than relying upon generic predictive variables [13].

Table 1. Historical Record Indicators Associated with Major Land Ownership Dispute Types

Dispute type	Documentary indicator	Spatial indicator	Temporal indicator	Likely data source
Boundary-overlap dispute	Conflicting survey plans	Parcel overlap	Multiple survey dates	Survey plans, cadastral maps
Duplicate-title dispute	Multiple title documents	Same parcel reference	Duplicate registration dates	Title registry
Ownership-chain discontinuity	Missing transfer records	Parcel continuity maintained	Ownership gaps	Deeds, conveyances
Parcel identity mismatch	Inconsistent parcel IDs	Incorrect parcel linkage	Administrative changes	Mutation records
Illegal subdivision	Unauthorised subdivision record	Unregistered parcel boundaries	Missing approval dates	Planning approvals
Encroachment claim	Boundary complaint	Building crosses parcel	Progressive occupation	Survey plans, satellite

Dispute type	Documentary indicator	Spatial indicator	Temporal indicator	Likely data source
		boundary		imagery
Survey coordinate conflict	Confeting coordinate values	Boundary displacement	Multiple survey epochs	Coordinate registers
Inheritance dispute	Conflicting probate records	Shared parcel ownership	Succession timeline	Probate documents
Registration-priority dispute	Competing registration entries	Same parcel	Conflicting registration sequence	Land registry

2.3 Sources of Error, Uncertainty and Record Degradation

Historical land records frequently contain multiple forms of uncertainty that complicate ownership verification and increase the difficulty of distinguishing genuine legal disputes from data-quality deficiencies [10]. Successive cadastral surveys may employ different coordinate reference systems, introducing systematic positional discrepancies when historical and contemporary survey records are compared without appropriate transformation procedures [6]. Earlier surveying instruments often possessed lower measurement precision than modern geospatial technologies, producing cumulative positional errors that propagate throughout historical cadastral archives [12]. Missing parcel identifiers, inconsistent numbering systems, and incomplete administrative records further weaken reliable linkage between historical and current land information systems [9]. Digitisation introduces additional uncertainty because scanning distortion, poor image quality, and document deterioration may alter the visual appearance of archived survey plans and legal records [14]. Ambiguous handwritten annotations, inconsistent spelling of landowner names, and variations in administrative terminology further complicate automated document interpretation and ownership reconstruction [8]. Unregistered property transfers and delayed cadastral updates frequently create temporal inconsistencies between actual ownership and officially recorded land information [11]. Surveyor misconduct, transcription mistakes, and intentional manipulation of legal documents may also generate evidence that superficially resembles legitimate ownership records while concealing fraudulent activities [13].

Consequently, analytical systems must distinguish ordinary data-quality limitations from evidence genuinely indicating ownership disputes or fraudulent transactions [7]. A simple record reliability score may therefore be expressed as:

$$R_i = \sum_{j=1}^{m} w_j \, q_{ij}$$

where R_i represents the reliability of record i, q_{ij} denotes the quality score assigned to criterion j, w_j represents the corresponding criterion weight, and

$$\sum w_j = 1$$

ensures that all weighting coefficients collectively equal unity [10]. This reliability measure provides an objective basis for evaluating evidential quality before machine-learning analysis is performed [6].

3. HISTORICAL SURVEY RECORD RECONSTRUCTION AND DATA ENGINEERING

3.1 Archival Acquisition, Digitisation and Quality Control

The reconstruction of historical parcel histories begins with systematic archival acquisition and quality assurance to ensure that documentary evidence is complete, traceable, and suitable for computational analysis [17]. The process commences with record inventory, during which survey plans, cadastral maps, field books, deeds, probate records, court judgments, mutation files, planning approvals, valuation records, and supporting administrative documents are identified, catalogued, and organised according to archival standards [14]. High-resolution document scanning converts fragile paper records into durable digital images while preserving the visual characteristics required for subsequent interpretation and verification [20]. Image enhancement techniques, including noise reduction, contrast adjustment, skew correction, stain removal, and resolution improvement, increase document readability and improve the performance of automated extraction methods [15]. Metadata capture records essential descriptive information such as document identifiers, creation dates, surveyors, registration authorities, storage locations, and document status, thereby facilitating efficient indexing and retrieval [18]. Georeferencing aligns scanned survey plans with recognised coordinate reference systems, allowing historical spatial information to be integrated with contemporary cadastral datasets [13]. Duplicate removal and version identification eliminate redundant records while distinguishing successive revisions from original documents, thereby preventing conflicting interpretations of the same parcel history [19]. Throughout the digitisation process, archival provenance must remain permanently associated with every extracted attribute, ensuring that each coordinate, ownership record, survey measurement, or legal statement can be traced directly to its original documentary source for evidential verification and legal accountability [16].

3.2 Textual Information Extraction from Survey and Ownership Documents

Historical survey records contain extensive textual information describing ownership, parcel identity, legal transactions, survey observations, and administrative decisions that must be converted into structured machine-readable data before computational analysis can be performed [18]. Optical Character Recognition (OCR) enables printed survey documents, title deeds, mutation forms, and registration records to be transformed into searchable digital text, while Handwritten Text Recognition (HTR) supports extraction from handwritten field books, annotations, survey notes, and historical registers that cannot be processed reliably using conventional OCR techniques [14]. Named-Entity Recognition (NER) identifies key entities including landowners, surveyors, institutions, parcel identifiers, administrative districts, and legal authorities that appear within documentary evidence [20]. Legal-language processing further extracts relationships among transactions, ownership rights, restrictions, inheritance events, and judicial determinations while preserving the contextual meaning of specialised legal terminology [16]. Automated extraction of survey numbers, owner names, registration dates, transaction histories, and parcel descriptions enables fragmented documentary evidence originating from different archival sources to be linked into coherent ownership histories [13]. Because historical records frequently contain inconsistent spelling, abbreviations, incomplete addresses, and changing parcel identifiers, entity-resolution algorithms are required to determine whether different documents refer to the same parcel or individual [19].

Entity similarity may be represented as:

$$S(a, b) = \alpha S_n + \beta S_a + \gamma S_d + \delta S_p$$

where $S_n$represents name similarity, $S_a$denotes address similarity, $S_d$represents document-reference similarity, $S_p$indicates parcel-description similarity, and

$$\alpha + \beta + \gamma + \delta = 1$$

ensures that the weighting coefficients collectively sum to one [15]. This similarity measure improves automated linkage of historical records while reducing duplication and ownership ambiguity across heterogeneous documentary collections [17].

3.3 Spatial Harmonisation of Historical Survey Plans

Historical survey plans often originate from different surveying epochs, coordinate systems, and mapping conventions, making spatial harmonisation essential before parcel histories can be reconstructed reliably [13]. Coordinate transformation converts historical survey information into contemporary reference systems, enabling direct comparison between archived plans and modern cadastral databases despite differences in measurement standards and geodetic frameworks [18]. Datum reconciliation further eliminates systematic positional discrepancies arising from successive coordinate reference systems adopted throughout different survey periods [20]. Georeferencing employs accurately surveyed control points to align historical plans with current spatial datasets while preserving the original geometric characteristics of parcel boundaries [14]. Polygon reconstruction converts bearings, distances, monument descriptions, and coordinate observations into complete parcel polygons suitable for spatial analysis [17]. Bearing and distance conversion standardises historical surveying measurements expressed using different units, notation systems, or surveying conventions across multiple decades [16]. Topological correction removes geometric inconsistencies including gaps, overlaps, sliver polygons, and disconnected boundaries that may otherwise compromise cadastral integrity [19]. Parcel boundary snapping subsequently aligns neighbouring parcel boundaries with contemporary cadastral layers, ensuring consistent spatial connectivity throughout reconstructed land records [15].

The affine transformation model is expressed as:

$$x' = a_0 + a_1 x + a_2 y$$
$$y' = b_0 + b_1 x + b_2 y$$

where the transformation coefficients adjust translation, rotation, scaling, and skew between historical and current coordinate systems [13]. Transformation accuracy is evaluated using the Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(x_i' - x_i)^2 + (y_i' - y_i)^2\right]}$$

which quantifies residual positional error following spatial alignment and provides an objective measure of georeferencing quality [20].

3.4 Temporal Parcel-Lineage Reconstruction

Following documentary extraction and spatial harmonisation, individual records must be linked chronologically to reconstruct the complete legal and spatial evolution of every parcel represented within the historical archive [19]. Parcel lineage is established by identifying ownership transfers recorded through deeds, conveyances, and registration transactions that legally transfer property rights between successive owners [14]. Inheritance events introduce additional ownership transitions resulting from probate proceedings and succession laws, while subdivision processes divide existing parcels into smaller landholdings that subsequently develop independent ownership histories [18]. Parcel consolidation combines adjoining properties into larger cadastral units, requiring historical parcel identities to be merged while preserving previous ownership relationships

[15]. Mortgage registration records provide evidence of temporary legal interests affecting ownership status, whereas boundary modifications resulting from resurveys, planning decisions, compulsory acquisition, or negotiated adjustments alter parcel geometry without necessarily changing ownership [20]. Revocation or cancellation of titles, together with court-directed reassignment of ownership, further modify legal parcel histories by invalidating previous ownership claims and establishing new legally recognised property rights [16].

These evolving relationships may be represented using a temporal graph:

$$G = (V, E, T)$$

where V represents owners, parcels, survey plans, and legal transactions, E denotes the legal or spatial relationships connecting those entities, and T records the period during which each relationship remained legally valid [17]. Temporal graph representation preserves both chronological sequence and evidential traceability, enabling complete reconstruction of parcel histories while providing a robust analytical foundation for detecting ownership inconsistencies, documentary contradictions, and emerging dispute risks across complex land administration systems [13].

Figure 2. Historical Survey Record Reconstruction Pipeline

4. DISPUTE-SENSITIVE FEATURE ENGINEERING AND ANOMALY DETECTION

4.1 Documentary Conflict Features

Documentary evidence provides one of the richest sources of information for identifying inconsistencies that may indicate emerging or existing land ownership disputes [24]. A primary indicator is the number of owners associated with a single parcel, since multiple concurrent ownership records often suggest unresolved succession issues, duplicate registrations, or conflicting legal claims [21]. Duplicate deed references constitute another important feature because identical deed numbers appearing in different ownership chains may indicate administrative errors or fraudulent document reuse [26]. Contradictory transfer dates, where ownership appears to change before a preceding transaction has been legally completed, represent temporal inconsistencies that interrupt legitimate ownership progression [19]. Missing transfer instruments similarly create discontinuities within reconstructed ownership histories by leaving undocumented gaps between successive legal owners [23]. Repeated title numbers assigned to different parcels or individuals may indicate registry inconsistencies or deliberate document manipulation [27]. Variations in owner-name spelling across historical records provide further evidence of possible identity ambiguity requiring entity-resolution verification [22]. Survey-plan revision frequency reflects repeated modifications to parcel boundaries or legal descriptions, while multiple registrations occurring within unusually short time intervals may signal contested ownership, accelerated administrative processing, or attempts to legitimise competing claims before legal resolution [20]. Collectively, these documentary variables provide measurable evidence describing the consistency and integrity of historical ownership records before spatial analysis is undertaken [25].

4.2 Spatial Conflict and Boundary-Inconsistency Features

Spatial inconsistencies provide direct evidence of disagreement between historical and contemporary representations of parcel boundaries and frequently reveal conflicts that remain hidden within documentary records alone [20]. Polygon overlap measures the extent to which neighbouring parcels occupy the same geographical space, thereby identifying potential boundary conflicts or duplicate registrations [27]. Boundary displacement quantifies positional differences between historical and current parcel limits resulting from resurveys, inaccurate measurements, environmental change, or unauthorised boundary modification [22]. Area inconsistency evaluates whether parcel size has changed unexpectedly without corresponding legal documentation, while coordinate deviation measures discrepancies between historical survey coordinates and contemporary cadastral positions following spatial harmonisation [25]. Parcel-centroid movement provides an additional indicator of systematic boundary migration by measuring shifts in the geometric centre of reconstructed parcel polygons across successive survey epochs [19]. Topological gaps identify discontinuities between neighbouring parcels that should share common boundaries but instead contain unintended spaces caused by mapping inconsistencies or digitisation errors [23]. Encroachment distance measures the extent to which structures, fences, or land occupation extend beyond legally recognised parcel boundaries, while conflicts with adjoining parcels identify incompatible spatial relationships that cannot coexist within a valid cadastral system [26].

Spatial similarity between historical and contemporary parcel geometry may be evaluated using the Intersection over Union (IoU):

$$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where higher values indicate greater spatial agreement between parcel representations [21].

Parcel area deviation may be expressed as:

$$D_A = \frac{|A_h - A_c|}{A_h} \times 100$$

where A_h represents historical parcel area and A_c denotes the current parcel area [24]. Large deviations may indicate subdivision, boundary alteration, surveying error, or potential ownership conflict requiring detailed investigation [27].

4.3 Temporal and Ownership-Lineage Features

Temporal reconstruction enables ownership histories to be analysed as evolving legal processes rather than isolated administrative events, thereby revealing inconsistencies that accumulate throughout successive ownership transitions [23]. Transfer frequency measures how often ownership changes occur within a specified period, with unusually frequent transfers potentially indicating speculative transactions, fraudulent activity, or unresolved ownership disputes [19]. Ownership duration evaluates the length of time each owner legally controls a parcel and helps distinguish stable ownership histories from unusually short or irregular possession periods [26]. Transaction chronology violations occur when recorded legal events appear in an impossible chronological sequence, such as ownership transfers preceding registration or inheritance occurring before documented ownership [22]. Simultaneous ownership claims identify overlapping periods during which multiple individuals appear to possess legal rights over the same parcel [25]. Missing ownership links reveal discontinuities within reconstructed ownership chains where expected transactions are absent from available records [21]. Sudden parcel-area changes without corresponding legal justification may indicate undocumented subdivision, consolidation, or survey inconsistencies, while prolonged registration delays highlight discrepancies between legal transactions and official cadastral updates [27]. The reappearance of previously cancelled titles further suggests administrative inconsistency or potential documentary manipulation requiring detailed legal examination [20].

Lineage continuity may be represented as:

$$L_c = \frac{N_v}{N_e}$$

where N_v denotes verified ownership transitions and N_e represents the expected transitions within the reconstructed ownership chain [24]. Lower values indicate greater probabilities of missing documentation, contradictory ownership evidence, or unresolved historical inconsistencies [19].

4.4 Unsupervised Detection of Previously Unknown Dispute Patterns

Although supervised learning requires labelled examples of known disputes, historical land administration records frequently contain incomplete, inconsistent, or entirely undocumented ownership conflicts, making unsupervised learning particularly valuable for discovering previously unidentified dispute patterns [27]. Isolation Forest algorithms identify anomalous parcel histories by recursively isolating observations that differ substantially from the majority of historical records, thereby highlighting unusual ownership or registration behaviour [20]. Local Outlier Factor (LOF) evaluates the density of neighbouring observations to detect parcels exhibiting abnormal documentary, temporal, or spatial characteristics relative to surrounding records [25]. Autoencoders employ deep neural networks to reconstruct normal parcel histories and identify anomalies through elevated reconstruction error, enabling subtle inconsistencies to be detected without requiring labelled dispute examples [22]. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) groups parcels exhibiting similar characteristics while identifying isolated observations that may represent unique ownership conflicts or fraudulent registrations [19]. One-Class Support Vector Machines establish decision boundaries describing normal parcel evolution and classify observations outside those boundaries as potential anomalies [26]. Graph anomaly detection further analyses parcel-lineage networks by identifying unusual ownership relationships, disconnected legal transitions, or unexpected structural patterns that deviate from typical ownership evolution [21].

An integrated anomaly score may be expressed as:

$$A_i = \lambda_1 D_i + \lambda_2 S_i + \lambda_3 T_i + \lambda_4 G_i$$

where D_i represents documentary anomaly, S_i denotes spatial anomaly, T_i indicates temporal anomaly, and G_i measures graph-relationship anomaly, subject to:

$$\sum \lambda_i = 1$$

ensuring that the weighting coefficients collectively sum to one [24]. This integrated score combines complementary evidence sources into a unified representation of dispute likelihood and supports prioritisation of parcels requiring detailed legal investigation [27].

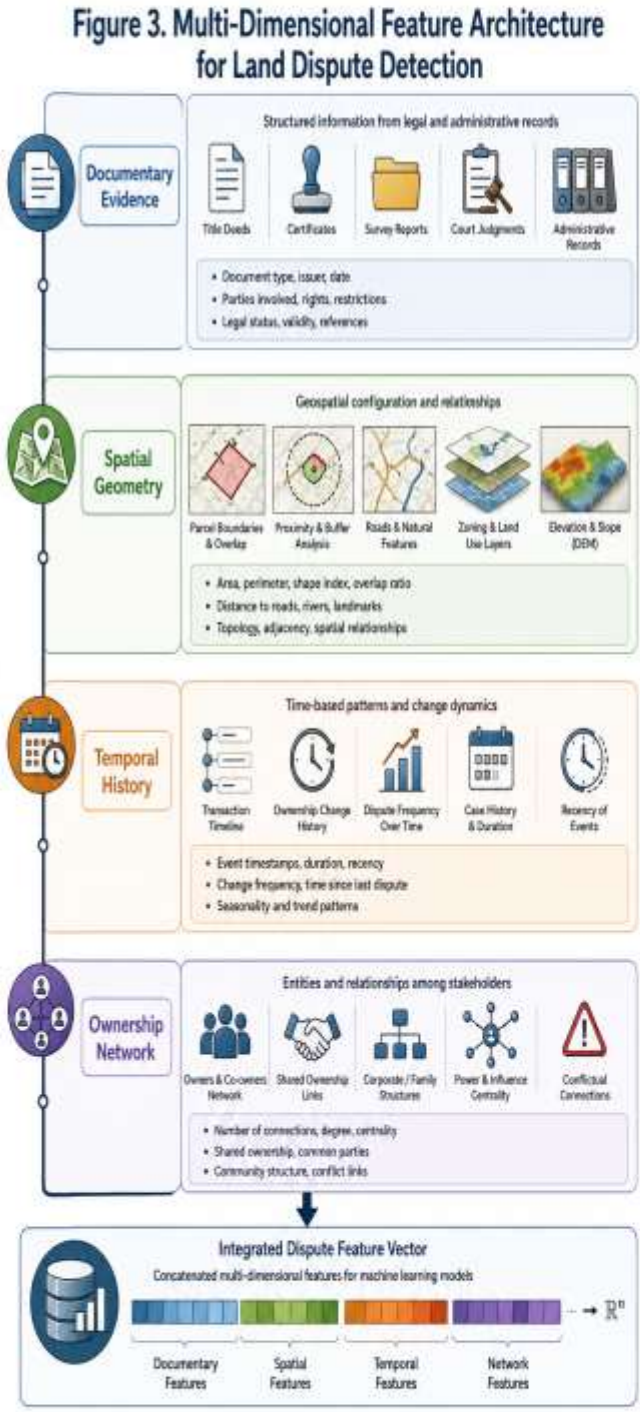

Figure 3. Multi-Dimensional Feature Architecture for Land Dispute Detection

Table 2. Proposed Features for Machine-Learning-Based Land Dispute Detection

Feature category	Variable	Measurement method	Expected dispute relationship	Data limitation
Documentary	Number of owners per parcel	Record aggregation	Higher values indicate competing ownership	Incomplete ownership records
Documentary	Duplicate deed references	Document matching	Duplicate references increase dispute likelihood	Registry inconsistencies
Documentary	Transfer-date conflicts	Chronological validation	Greater inconsistency increases legal uncertainty	Missing historical dates
Spatial	Polygon overlap	GIS overlay analysis	Larger overlap indicates boundary conflict	Georeferencing error
Spatial	Area deviation	Historical-current comparison	Greater deviation suggests parcel alteration	Legacy survey precision
Spatial	Encroachment distance	Boundary measurement	Larger encroachment increases ownership conflict	Incomplete structure mapping
Temporal	Transfer frequency	Transaction history analysis	Excessive transfers increase dispute probability	Missing transactions
Temporal	Lineage continuity	Ownership-chain reconstruction	Lower continuity indicates documentary gaps	Incomplete archival records
Network	Ownership-network anomaly	Graph analysis	Higher anomaly indicates irregular parcel history	Sparse relationship data

5. MACHINE LEARNING MODEL DEVELOPMENT AND COMPARATIVE EVALUATION

5.1 Dispute Labelling and Training Dataset Construction

The effectiveness of supervised machine-learning models depends on the availability of accurately labelled training datasets that distinguish disputed parcels from legally uncontested landholdings [30]. Confirmed ownership disputes may be identified using court decisions that establish judicial determinations of ownership, land tribunal records documenting formal dispute proceedings, registry objections submitted during title registration, administrative cancellation records arising from fraudulent or invalid registrations, surveyor investigation files describing technical boundary inconsistencies, and mediation outcomes recording negotiated dispute resolutions outside formal litigation [26]. These complementary sources provide authoritative evidence linking documentary inconsistencies with verified legal outcomes and therefore constitute reliable ground truth for predictive modelling [32]. Each reconstructed parcel history may subsequently be labelled according to confirmed dispute status, probable ownership conflict, or uncontested ownership, thereby supporting supervised learning across multiple levels of legal certainty [27]. Nevertheless, historical dispute datasets frequently exhibit substantial class imbalance because disputed parcels represent only a small proportion of registered landholdings, while uncertain legal outcomes introduce ambiguous class labels that may reduce predictive reliability [29]. Addressing these challenges requires balanced sampling techniques, uncertainty-aware labelling strategies, expert verification, and continuous updating of training datasets as additional legal determinations become available, thereby improving model robustness and reducing classification bias [25].

5.2 Supervised Classification Models

Supervised classification algorithms provide a systematic means of estimating the likelihood that reconstructed parcel histories contain documentary, spatial, temporal, or administrative evidence consistent with land ownership disputes [28]. Logistic regression establishes an interpretable probabilistic baseline by estimating the contribution of individual explanatory variables while allowing legal practitioners to understand the influence of specific evidential factors on dispute probability [31]. Decision trees provide transparent rule-based classification that mirrors human decision-making by recursively partitioning parcel records according to documentary and spatial characteristics associated with ownership conflict [25]. Random Forest algorithms extend this approach by combining numerous decision trees, thereby improving prediction accuracy and reducing sensitivity to noisy historical records [32]. Support Vector Machines (SVMs) effectively classify complex ownership histories by identifying optimal decision boundaries within multidimensional feature spaces that contain nonlinear documentary and spatial relationships [27]. Extreme Gradient Boosting (XGBoost) further improves predictive performance through iterative optimisation that captures subtle interactions among historical ownership variables while reducing overfitting [30]. Artificial Neural Networks (ANNs) provide additional flexibility by learning highly nonlinear relationships from extensive multi-source datasets integrating textual, spatial, temporal, and administrative evidence [26].

The probability that a parcel contains confirmed or probable ownership conflict may be expressed as:

$$P(Y=1 \mid X)=\frac{1}{1+\exp[-(\beta_0+\beta_1X_1+\cdots+\beta_nX_n)]}$$

where $Y=1$denotes a parcel with confirmed or probable ownership conflict, $X_1,\ldots,X_n$represent engineered dispute features, and $\beta_0,\beta_1,\ldots,\beta_n$are parameters estimated during model training [29]. The resulting probability provides a quantitative basis for prioritising legal investigation and cadastral verification [31].

5.3 Natural Language and Document-Based Models

Many ownership conflicts originate from inconsistencies embedded within legal documents rather than from observable geometric discrepancies, making natural language processing an essential component of intelligent land administration [32]. Transformer-based language models provide contextual understanding of deeds, conveyances, probate records, court judgments, and administrative correspondence by capturing semantic relationships extending beyond simple keyword matching [27]. Document embeddings transform lengthy legal records into numerical representations that preserve linguistic meaning while supporting efficient comparison across extensive historical archives [30]. Legal-text classification models automatically distinguish normal ownership transactions from documents exhibiting characteristics commonly associated with ownership disputes, fraudulent registrations, or administrative inconsistencies [26]. Semantic contradiction detection identifies conflicting legal statements appearing across different ownership records, while similarity analysis compares successive deeds to identify duplicated language, altered ownership clauses, or inconsistent transaction details [28]. Automated comparison of parcel descriptions further detects subtle discrepancies involving boundary descriptions, neighbouring parcels, measurements, easements, and ownership conditions that may remain undetected using spatial analysis alone [25]. These document-centred models therefore complement geometric analysis by identifying legal contradictions embedded within textual evidence that cannot be inferred solely from cadastral maps or survey coordinates [31].

5.4 Graph Machine Learning for Ownership-Network Analysis

Ownership histories naturally form interconnected networks linking parcels, landowners, surveyors, legal representatives, witnesses, financial institutions, and registration authorities through successive transactions and legal relationships [29]. Graph Neural Networks (GNNs) exploit these interconnected structures by learning patterns that extend beyond individual parcel histories and capturing dependencies among related entities throughout historical land administration systems [32]. Link prediction techniques estimate previously unobserved legal relationships, thereby identifying missing ownership transitions or undocumented connections that may indicate incomplete historical records [26]. Community detection algorithms identify clusters of closely related parcels, owners, or intermediaries whose recurring interactions may reveal organised patterns of fraudulent registration or systematic ownership manipulation [30]. Repeated ownership intermediaries, unusually connected surveyors, or recurrent legal representatives appearing across multiple disputed parcels provide valuable indicators of elevated ownership risk requiring detailed investigation [27]. Graph-based analysis further models complex surveyor–parcel–owner networks by incorporating witnesses, registration officials, and institutional relationships that conventional tabular datasets cannot adequately represent [25]. Through these capabilities, graph machine learning identifies unusual ownership structures and hidden evidential relationships that substantially improve historical dispute detection beyond traditional document-based analysis [31].

5.5 Ensemble Dispute-Risk Model

Individual machine-learning models capture different dimensions of ownership conflict, making ensemble learning an effective strategy for integrating complementary evidence into a unified dispute assessment [30]. Documentary, spatial, temporal, and graph-based predictions may therefore be combined to produce a comprehensive dispute-risk score representing multiple forms of historical inconsistency simultaneously [28]. The proposed ensemble model is expressed as:

$$DRS=w_dP_d+w_sP_s+w_tP_t+w_gP_g$$

where DRSrepresents the overall dispute-risk score, $P_d$denotes documentary-model probability, $P_s$represents spatial-model probability, $P_t$indicates temporal-model probability, and P_g corresponds to graph-model probability, subject to:

$$\sum w = 1$$

ensuring that the weighting coefficients collectively sum to one [32]. This integrated framework produces balanced, evidence-based ownership risk estimates suitable for prioritising investigation and legal review [26].

5.6 Model Validation and Performance Assessment

Reliable deployment within land administration requires rigorous evaluation of predictive performance using both statistical and operational measures [27]. Classification performance may be assessed using:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

where TP, FP, and FN represent true positives, false positives, and false negatives, respectively [29]. Additional evaluation should include overall accuracy, Receiver Operating Characteristic–Area Under the Curve (ROC–AUC), precision–recall curves, calibration analysis, spatial cross-validation across different cadastral regions, and temporal holdout testing using future ownership records not included during model training [31]. Together, these validation procedures ensure predictive reliability while supporting transparent deployment within legally accountable land administration systems [25].

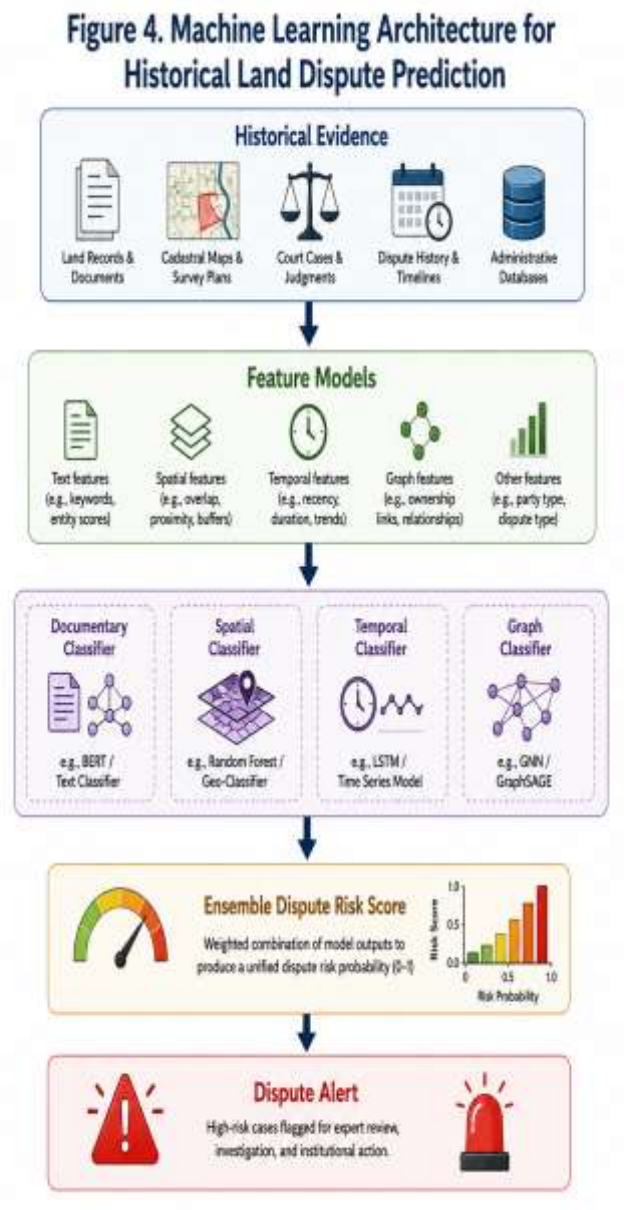

Figure 4. Machine Learning Architecture for Historical Land Dispute Prediction

Table 3. Comparative Evaluation Framework for Land Dispute Detection Models

Model	**Input type**	**Interpretability**	**Class-imbalance tolerance**	**Computational demand**	**Evaluation metric**
Logistic Regression	Documentary and tabular features	Very High	Moderate	Low	ROC–AUC, Precision
Decision Tree	Structured dispute	High	Moderate	Low	Accuracy, F1-

Model	**Input type**	**Interpretability**	**Class-imbalance tolerance**	**Computational demand**	**Evaluation metric**
	features				score
Random Forest	Multi-source structured data	High	High	Moderate	ROC–AUC, Recall
Support Vector Machine	Engineered feature vectors	Moderate	Moderate	Moderate	Precision, F1-score
XGBoost	Integrated documentary, spatial and temporal features	Moderate	High	High	ROC–AUC, Precision–Recall
Artificial Neural Network	Large multi-source datasets	Low	High	Very High	Accuracy, ROC–AUC
Transformer Language Model	Legal and ownership documents	Moderate	Moderate	Very High	F1-score, Precision
Graph Neural Network	Ownership-network graphs	Moderate	High	High	ROC–AUC, Link Prediction Accuracy

6. EXPLAINABILITY, LEGAL TRACEABILITY AND INSTITUTIONAL APPLICATION

6.1 Explainable Artificial Intelligence for Dispute Decisions

The adoption of machine learning within land administration requires predictive models to produce transparent and legally interpretable explanations rather than opaque risk scores that cannot be justified during administrative or judicial review [34]. Explainable Artificial Intelligence (XAI) provides this transparency by identifying the documentary, spatial, temporal, and relational evidence that most strongly influences each dispute prediction [29]. SHapley Additive exPlanations (SHAP) quantify the contribution of every feature to the final prediction, enabling investigators to determine whether a parcel was classified as high risk because of polygon overlap, duplicate registration, broken ownership lineage, conflicting transfer dates, or multiple concurrent ownership claims [31]. Global feature-importance analysis identifies the variables that consistently influence predictions across the entire dataset, while local explanations clarify the specific reasons underlying an individual parcel assessment [35]. Counterfactual explanations further strengthen interpretability by indicating how a prediction would change if contradictory evidence were removed or corrected, thereby assisting investigators in distinguishing genuine ownership conflicts from data-quality problems [30]. Evidence-ranking mechanisms prioritise the documentary and spatial records contributing most strongly to the prediction, allowing human reviewers to evaluate the most influential evidence before reaching legal conclusions [33]. Consequently, machine learning functions as an evidence-support mechanism whose recommendations remain subject to professional assessment and institutional oversight [28].

6.2 Evidential Traceability and Human-in-the-Loop Verification

Institutional confidence in predictive land administration depends upon complete evidential traceability linking every analytical output to its original documentary and spatial sources [30]. Each dispute alert should therefore provide direct access to the original scanned record image, extracted textual information, historical survey plans or cadastral maps, georeferencing and transformation accuracy statistics, reconstructed ownership-chain evidence, model confidence scores, and the neighbouring parcels that influenced the analytical decision [34]. Such traceability enables surveyors, land administrators, legal practitioners, and investigators to independently verify both the underlying evidence and the computational processes that generated the dispute alert [29]. Human-in-the-loop verification remains essential because legal ownership frequently depends upon contextual interpretation, statutory provisions, judicial precedent, and documentary evidence that cannot be fully represented within computational models alone [35]. Accordingly, the proposed framework supports investigators by organising, analysing, and prioritising historical evidence rather than automatically determining ownership rights or replacing professional legal judgment during dispute resolution [31].

6.3 Operational Integration into Land Administration

Practical implementation requires predictive dispute-detection systems to integrate seamlessly with existing institutional workflows responsible for land governance and property administration [33]. Land registries may employ predictive risk scores during title registration to identify applications requiring additional documentary verification before registration is completed [28]. Survey departments can utilise reconstructed parcel histories to support boundary

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verification, resurvey activities, and cadastral updating, while courts and land tribunals may use explainable evidence summaries to facilitate efficient examination of disputed ownership histories [35]. Planning authorities benefit through improved identification of ownership inconsistencies before approving subdivision, consolidation, or development applications [30]. Conveyancing systems may automatically identify documentary anomalies during property transactions, and specialised fraud-investigation units can prioritise parcels exhibiting elevated probabilities of document manipulation, duplicate registration, or coordinated ownership fraud [32].

6.4 Ethical, Privacy and Governance Requirements

Responsible deployment of machine learning within land administration requires governance frameworks that protect legal rights while maintaining public confidence in automated decision-support systems [31]. Personal-data protection should ensure that ownership information is processed securely and accessed only by authorised institutions in accordance with applicable privacy legislation [34]. Historical datasets should be evaluated for inherited biases that may disadvantage particular communities, including customary-tenure systems that have traditionally been underrepresented within formal cadastral records [29]. Regular assessment is also required to minimise algorithmic discrimination and ensure equitable treatment of different ownership groups [35]. Comprehensive access controls, immutable audit trails, and clearly defined model-accountability mechanisms should document every analytical decision, thereby strengthening transparency, institutional responsibility, and long-term confidence in intelligent land administration systems [33].

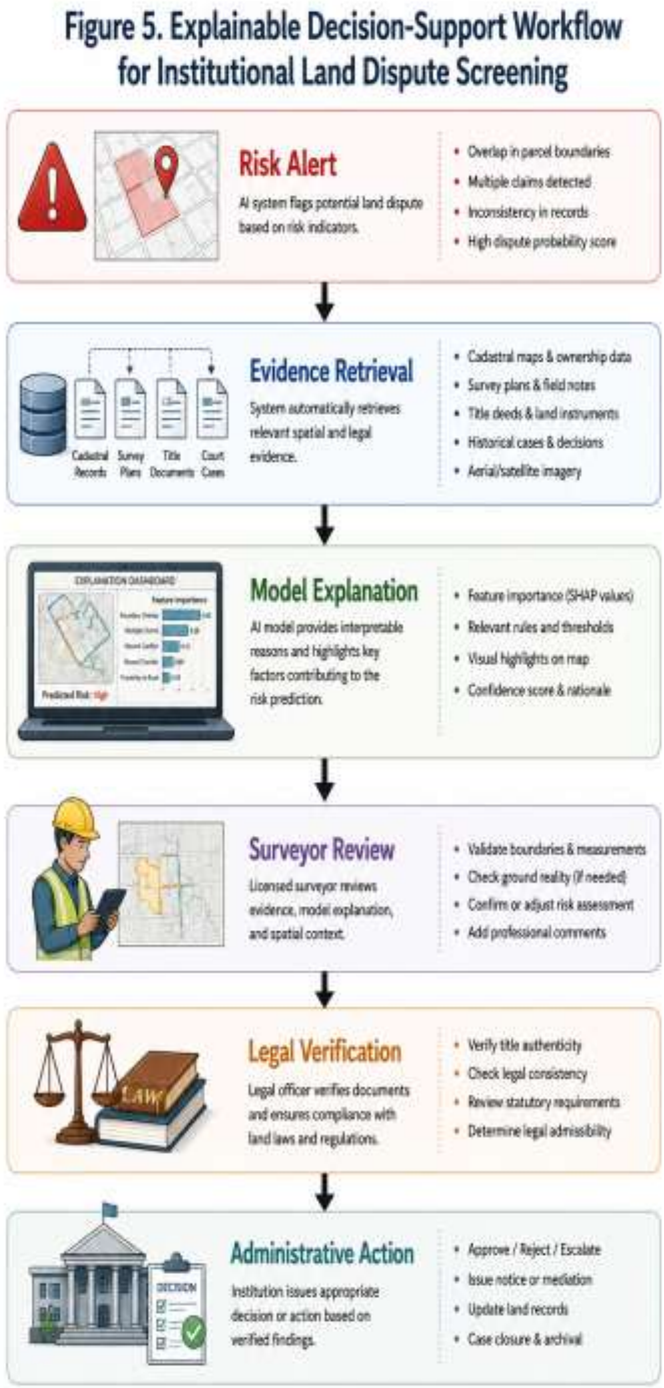

Figure 5. Explainable Decision-Support Workflow for Institutional Land Dispute Screening

7. DISCUSSION AND CONCLUSION

7.1 Methodological and Practical Implications

The proposed framework demonstrates that effective land ownership dispute detection requires the integration of historical documentary evidence, spatial analytics, natural language processing, and graph-based machine learning rather than reliance on isolated cadastral records or individual legal documents [34]. Historical survey records provide the temporal foundation for reconstructing parcel evolution, while spatial harmonisation identifies geometric inconsistencies that may indicate boundary conflict or undocumented parcel modification [32]. Natural language processing complements spatial analysis by extracting legal relationships, ownership transfers, and documentary contradictions embedded within deeds, probate records, and court documents that cannot be inferred from geometry alone [35]. Graph learning further strengthens predictive capability by modelling complex interactions among owners, surveyors, parcels, registration officials, and legal transactions, thereby revealing hidden ownership patterns and suspicious relationship networks [33]. Collectively, these complementary analytical approaches enable earlier identification of high-risk parcels, substantially reduce manual archival searches, improve prioritisation of field investigations, support more reliable title verification, enhance cadastral updating, and contribute to more proactive land administration capable of resolving inconsistencies before they develop into costly legal disputes [34].

Despite these advantages, several practical limitations remain. Historical archives are frequently incomplete or physically degraded, reducing the continuity of reconstructed ownership histories [35]. Ground-truth labels derived from judicial decisions and administrative records may not capture every disputed parcel, thereby introducing uncertainty into supervised learning [32]. Variations in historical surveying accuracy, institutional fragmentation between land administration agencies, and differences in legal frameworks across jurisdictions further affect model transferability and operational deployment [33]. Addressing these challenges requires continued collaboration among surveying professionals, legal institutions, geospatial scientists, and machine-learning researchers to ensure that predictive systems remain technically reliable and institutionally credible [34].

7.2 Conclusion and Research Outlook

Land ownership disputes should be understood as multi-source evidence inconsistencies that emerge through interactions among historical documents, spatial records, ownership histories, and administrative processes rather than as isolated boundary disagreements. By reconstructing parcel lineage, integrating documentary and spatial evidence, and applying explainable machine-learning models, it becomes possible to identify dispute-prone landholdings before inconsistencies escalate into formal litigation. Such an approach supports preventive land administration by strengthening evidence verification, improving institutional efficiency, and enhancing confidence in cadastral decision-making.

Future research should investigate multimodal foundation models capable of jointly analysing maps, legal documents, survey plans, and textual records; cross-jurisdictional validation to evaluate model generalisability across different legal systems; federated learning for secure inter-agency collaboration; uncertainty-aware prediction frameworks; automated interpretation of historical maps; improved integration of customary tenure evidence; and longitudinal evaluation of dispute-prevention outcomes to determine the long-term effectiveness of intelligent land administration systems in reducing ownership conflicts and strengthening property governance.

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