*Construction Focus, Vol 16, No 1, (2023) 41 – 53*

# EVALUATION OF THE INTERRELATIONSHIPS AMONG THE CAUSES OF WALL CRACKS IN RESIDENTIAL BUILDINGS USING ASSOCIATION RULE MINING

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## ABSTRACT

*Building cracks significantly impact structural integrity, maintenance costs, and occupant satisfaction. While numerous studies have investigated the causes of cracks, determining primary contributors remains complex due to the interconnected nature of underlying factors. This study examines the synergistic relationships among the causes of wall cracks in residential buildings to identify dominant crack contributing factors. 160 residential blocks at Ahmadu Bello University's Area F staff quarters were surveyed to identify buildings that exhibits cracks. 73 buildings exhibiting visible cracks were purposively selected for detailed evaluation. Visual inspection was conducted to measure crack dimensions on all the 73 selected buildings. In addition, systematic evaluation was conducted using a checklist to identify and evaluate crack-inducing factors. Singular cause analysis (SCA) and Association Rule Mining (ARM) technique were used to analyse the data. The SCA identified three predominant crack causes: root growth (29.21%), improper landscaping (22.28%), and drought conditions (17.82%). More so, ARM technique implemented through RapidMiner software demonstrated strong associations between the identified causes of cracks, with root growth showing complete correlation (confidence: 1.00) when combined with drought and roof leakage effects (lift: 1.237), indicating significant multiplicative impacts. These findings highlight the importance of considering combined environmental and structural factors in crack formation. Based on these insights, the study recommends implementing strategic vegetation management plans, including proper tree placement protocols to mitigate root-related structural damage. The research has contributed by evaluating the complex interactions between multiple crack-inducing factors, offering a foundation for data-driven solutions for proactive wall crack management in residential buildings.*

**KEYWORDS:** *Association Rule Mining, Evaluation, Interrelationships, Residential Buildings, Wall Cracks.*

## INTRODUCTION

The persistent issue of cracks in buildings represents a global challenge that affects structural performance, aesthetic quality, and long-term durability. As noted by Arvind (2017), these structural imperfections occur when induced stresses exceed the inherent strength capacity of the material. The origins of such stresses are multifaceted, arising from both external factors – including dead and live loads, wind action, seismic activity, and foundation settlement – and internal factors such as thermal fluctuations, moisture variation, and chemical reactions.

Cracks typically manifest as complete or partial separations within concrete matrices, resulting from tensile stresses that surpass the material's capacity (Yunusa et al., 2015). While complete prevention of cracks remains a challenge, uncontrolled cracking can lead to consequences extending beyond aesthetic deterioration. Such cracks can compromise structural integrity, accelerate material degradation, and significantly increase maintenance costs (Arvind, 2017).

Despite extensive research into individual factors causing cracks in buildings (Aljassani & Han, 2013; Lee et al., 2019; Park et al., 2020), a critical knowledge gap persists regarding the complex interrelationships among multiple contributing elements. As Lee et al. (2019) emphasize, a holistic understanding of crack formation requires an analysis of the synergistic effects between various factors causing cracks.

This study specifically investigates wall cracks in the residential quarters of Ahmadu Bello University (Area F), where preliminary observations indicate significant cracking issues. Although previous studies have catalogued individual causes, interactions among factors such as root growth, soil conditions, roof or plumbing leakages, and moisture variation remain unexplored in this context. The present research employs Association Rule Mining (ARM) – an advanced data mining technique (Kamsu-Foguem et al., 2013a) – to evaluate and quantify the relationships between multiple crack-inducing factors.

The application of ARM in construction defect analysis represents a major advancement toward data-driven decision-making in the built environment. Unlike traditional methods that examine isolated causes, ARM uncovers hidden relationships among multiple interacting factors (Park et al., 2020). By identifying co-occurring variables and generating interpretable, rule-based insights, ARM supports preventive maintenance, risk prediction, and informed decision-making throughout a building's lifecycle. Overall, ARM marks a shift from reactive to proactive defect management, enhancing the durability, safety, and sustainability of buildings, especially in resource-constrained tropical settings (Lee et al., 2019).

By moving beyond singular causation approaches, this research aims to evaluate the interrelationships among multiple crack-inducing factors with a view to providing a foundation for proactive defect management in buildings. Additionally, the study seeks to establish a comprehensive basis for understanding the complex interrelationships among the causes of wall cracks, thereby facilitating more effective prevention and remediation approaches.

## LITERATURE REVIEW

### Causes of Wall Cracks

Wall cracks in buildings result from a complex interplay of structural, environmental, material, and human-related factors (Chitte & Sonawane, 2018). Fundamentally, cracks appear when the tensile stresses in structural components exceed their material strength, leading to separation along planes of weakness. According to Gurmu et al. (2020), the most frequent causes of cracking in ground floor systems of low-rise residential buildings include inadequate site drainage, poor soil drainage, drought, plumbing leaks, tree root activity, and inappropriate landscaping. Using inspection reports from 250 residential buildings in Melbourne, the authors identified site and soil drainage deficiencies as the two most significant causes of distress, while landscaping had a lesser effect.

Environmental conditions, particularly drought-induced soil shrinkage and swelling, are major contributors to wall and slab cracking. Soils with high clay content are especially vulnerable to volume change during dry and wet cycles (Corti et al., 2011; Toll et al., 2012). Drought reduces soil moisture, leading to differential settlement and wall movement (Wiltshier, 2007).

Similarly, plumbing leakages and defective surface drainage can cause localized soil saturation, erosion, and swelling beneath foundations, leading to cracking (El-Garhy & Wray, 2006; Mokhtari & Dehghani, 2012). Poor drainage design, water ponding, and inadequate slope around buildings were also found to exacerbate structural distress (Zumrawi et al., 2017).

The influence of tree roots on soil moisture variation is another critical factor. Trees extract water from expansive soils, causing localized shrinkage and differential settlement near foundations (McLean, 2009; Li & Guo, 2016). These effects are often more pronounced in reactive soils and temperate climates (Biddle, 2001). Subsurface drainage deficiencies further compound the problem by preventing adequate moisture control, while poor landscaping and overwatering can aggravate foundation instability (Murphy, 2010; Houston et al., 2011).

Collectively, these findings indicate that wall cracks are seldom caused by a single factor but rather by the interaction of multiple environmental and workmanship-related influences (Gurmu et al., 2020). Understanding these interdependencies provides a necessary foundation for developing mitigation strategies to improve the structural integrity of buildings.

**Use of Association Rule Mining Technique in Construction**

The adoption of Association Rule Mining (ARM) represents a significant step toward data-driven defect analysis in the construction industry. ARM uncovers if – then relationships between variables revealing hidden patterns among categorical datasets without predefined hypotheses (Han et al., 2011). Lee et al. (2019) integrated ARM with Social Network Analysis (SNA) for construction defect analysis using 2,949 defect records. Their study demonstrated that managerial issues – such as "inadequate protection" and "interference from other trades" – were central defect causes. Gurmu et al. (2020) extended this application to ground-floor systems, using ARM to identify co-occurring defect patterns across inspection data. They found that "poor site drainage" and "soil drainage deficiency" exhibited the highest out-degree centrality, signifying their systemic impact on building distress.

Subsequent studies have diversified ARM applications. Park et al. (2020) analyzed 9,054 non-conformance records to derive defect-generation rules validated by domain experts; Cheng et al. (2015) introduced a GA-based multi-level ARM to enhance rule accuracy; Ayhan et al. (2020) used ARM to correlate accident attributes; and Rith and Lee (2021) applied it to evaluate reflective cracking in asphalt pavements. More recently, Kim et al. (2023) used ARM to extract post-handover defect association rules in apartment buildings, demonstrating its scalability to large datasets. These studies collectively establish ARM as a robust analytical tool for discovering latent relationships among construction defects and operational factors, facilitating predictive maintenance and evidence-based quality management (Kamsu-Foguem et al., 2013b; Lee et al., 2019; Wu & Liu 2021).

**Advantages of ARM for Construction Defect Analysis**

The primary advantage of ARM is its ability to process large, non-numeric datasets and reveal complex multi-factor associations without prior modeling assumptions (Lee et al., 2019). It quantifies relationships using support, confidence, and lift, metrics that measure frequency, reliability, and significance of associations. This makes ARM particularly suited to defect log analysis, where most variables (e.g., defect type, location, cause) are qualitative (Han et al., 2011; Cheng et al., 2015). Additionally, combining ARM with visualization techniques such as SNA enhances interpretability by mapping relationships among defects, as shown in both Lee et al. (2019) and Gurmu et al. (2020). Nevertheless, researchers emphasize that ARM's effectiveness in construction depends on context-specific calibration and expert validation (Lee et al., 2019; Park et al., 2020).

## METHODOLOGY

Quantitative research method was adopted for the study. From the total population of 160 residential buildings in Area F staff quarters at Ahmadu Bello University, Zaria, purposive sampling technique was used to identify 73 buildings exhibiting visible external wall cracks. The data collection process involved two key phases. Reconnaissance survey - a preliminary assessment of building conditions and their immediate environments was conducted to identify potential crack-inducing factors. These included; vegetation impact (tree root growth); soil drainage characteristics; site drainage conditions; drought indicators; landscaping features and plumbing leakage evidence.

Also, a structured building inspection using a checklist was carried out. Each selected building underwent systematic evaluation to identify measure and record the visible wall cracks in the building. The Inspection was carried out by measuring the width of the crack using a tape, the individual cracks were marked and assigned to a category. The cracks severity was classified according to the width-based categorisation system established standards by Burland and Day (1977). The cracks inducing factors were also identified using the checklist.

Association Rule Mining (ARM) technique, a robust data mining technique particularly effective for identifying hidden relationships in categorical datasets (Kamsu-Foguem et al., 2013a; Witten et al., 2013) was used to evaluate the interrelationships between the cracks inducing factors. The ARM technique was implemented using RapidMiner software with the aid of the Apriori algorithm. Three principal analytical metrics were used to evaluate rule significance. These metrics are: 'Support', 'Confidence' and 'Lift'. The rules are all derived using ARM.

'Support' measures rule frequency in the dataset. It is the probability value (i.e., A → B) that A occurs when B occurs within the dataset and is obtained using Equation (1). The "Support" value is an index to measure how frequently two causes occur simultaneously, and a standard to determine how important the rules are (Park et al., 2020; Lee et al., 2019). 'Confidence' indicates rule reliability (conditional probability). It is a conditional probability value that "A" is generated when "B" is generated in the 'A → B' relationship and is obtained using Equation (2). 'Confidence' is a standard to present how much the rules can be trusted. Owing to the "Support" and "Confidence" being probability values, the closer they are to 1, the more connection they have (Park et al., 2020; Lee et al., 2019). 'Lift' assesses rule strength beyond random chance (Park et al., 2020; Lee et al., 2019). It is a measure that denotes how much the conditional probability of "A" increases when "B" is generated from the probability of "B" relative to the total, and is obtained from Equation (3) (Brijs et al., 2003). Thus, it depicts how much "A" influences the probability of "B" in the "A → B" relationship. The "Lift" value can be used to infer only those rules with higher correlations in the 'A → B' relationship. If the "Lift" > 1, it is considered to be in a positive correlation, and if "Lift" = 1, it is regarded as an independent relationship, and if it is between 0 and 1 (i.e., 0 < "Lift" < 1), it is a negative correlation with a low relationship.

$$\text{Support}(a \rightarrow b) = P(a \cap b) \ldots\ldots\ldots\ldots\ldots\ldots \text{Equation (1)}$$

$$\textbf{Confidence}(\mathbf{a} \rightarrow \mathbf{b}) = \mathbf{P}(\mathbf{a}|\mathbf{b}) = \frac{\boldsymbol{P(a \cap b)}}{\boldsymbol{P(a)}} \ldots\ldots\ldots\ldots\ldots \textbf{Equation (2)}$$

$$\text{Lift}(a \rightarrow b) = \frac{P(a|b)}{P(a)} = \frac{P(a \cap b)}{P(a)P(b)} \ldots\ldots\ldots\ldots\ldots \text{Equation (3)}$$

Interpretation guidelines:

- Lift > 1: Positive correlation (complementary factors)

- Lift = 1: Independent factors

- 0 < Lift < 1: Negative correlation (substitute factors)

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Implementation Parameters:

The analysis employed the following operational parameters:

- Minimum support threshold: 0.5 (50%)

- Minimum confidence threshold: 0.6 (60%)

- Maximum antecedent/consequent items: 3

## RESULTS AND DISCUSSION

### Reconnaissance Survey

The preliminary reconnaissance survey was conducted to identify and confirm the presence of crack inducing factors in the survey area. findings revealed presence of some critical environmental factors contributing to wall crack formation as presented in Table 1

**Table 1: Preliminary survey result for crack inducing factors**

| S/N | Crack inducing factors noticed | Yes | | No | |
|---|---|---|---|---|---|
| | | Frequency | % | Frequency | % |
| 1 | Mature trees in close proximity to building | 59 | 81 | 14 | 19 |
| 2 | Inadequate vegetation buffers | 45 | 62 | 28 | 38 |
| 3 | Improper site grading leading to moisture accumulation within building vicinity | 38 | 52 | 35 | 48 |
| 4 | Poor drainage system within building vicinity | 12 | 16 | 61 | 84 |
| 5 | Visible presence of silt-clay soil composition | 67 | 92 | 6 | 8 |

From Table 1, Mature trees, in some cases root systems visibly affecting the buildings were observed in close proximity to 59 (81) % of the buildings. In addition, inadequate vegetation buffers were noticed in 45 (62%) of the buildings. Moreover, only 38 (52%) out of the 73 cases exhibited improper grading which could lead to moisture accumulation. More so, in 12 (16%) out of the 73 cases, poor drainage systems are noticed which could contribute to water flooding around the buildings. Lastly 67 (92%) of the 73 cases show visible presence of silt-clay soil composition. This implies that, the result shows presence of many factors that could result to crack around the buildings.

### Main Buildings Inspection

73 buildings with visible cracks were purposively selected for the main survey. The buildings were inspected to identify, measure and categorise the nature of

cracks present in the buildings. and the result is presented in Table 2

**Table 2: Crack categorisation**

| Crack Width (mm) | Severity Class | Structural Impact | Frequency | (%) |
|---|---|---|---|---|
| <2 | Very Slight | Aesthetic | 14 | 19.18 |
| 2-5 | Slight | Aesthetic | 28 | 38.36 |
| 5-15 | Moderate | Serviceability | 18 | 24.66 |
| 15-25 | Severe | Serviceability | 8 | 10.96 |
| >25 | Very Severe | Stability | 5 | 6.57 |

Table 2 presents the classification system adopted in this study to categorize the cracks in the surveyed buildings according to their severity and structural impact, following the criteria established by Burland and Day (1977). Based on the measured crack widths, the frequency distribution across the buildings was determined. The results show that 57.54% of the cracks fell within the range affecting only the aesthetics of the buildings (<5 mm), while 35.62% were within the range impacting both aesthetics and serviceability (5-25 mm). A smaller proportion, 6.54%, represented critical structural concerns requiring immediate intervention (>25 mm). These findings indicate that the majority of cracks primarily affect the visual appearance of the buildings, whereas a limited number pose significant structural risks due to their severity.

**Singular Cause Approach for Assessing the Factors Causing Cracks**

Singular case approach was used to identify the causes of cracks in the building. Each factor was independently assessed based on observed frequencies and corresponding percentages as presented in Table 3.

**Table 3: Singular case causes of cracks in the buildings**

| Rank | Factor | Frequency | Percentage |
|---|---|---|---|
| 1 | Root Growth | 59 | 29.21% |
| 2 | Inadequate Landscaping | 45 | 22.28% |
| 3 | Drought | 36 | 17.82% |
| 4 | Water leakages from Roof | 27 | 13.36% |
| 5 | Plumbing Leakages | 17 | 8.42% |
| 6 | Surface Drainage | 12 | 5.94% |
| 7 | Soil Drainage | 6 | 2.97% |
| 8 | Excess Load on Walls | 0 | 0.00% |

Results from Table 3 indicates that root growth was the predominant factor, accounting for 29.21% of cases, followed by inadequate landscaping (22.28%) and drought conditions (17.82%). Collectively, vegetation- and water-related factors contributed to 64.85% of all observed cases. Notably, no instances of load-bearing wall overstress were identified. This finding suggests that root growth, inadequate landscaping, and drought – representing a combined 69.31% of occurrences – are the most significant contributors to wall cracking in the studied buildings.

## Association Rule Mining Results

Table 4 presents the transformed survey data in matrix format. This was generated from the raw data obtained.

**Table 4: Transformed data into sparse matrix**

| | Root Growth | Surface Drainage | Soil Drainage | Drought | Landscaping | Plumbing Leakages | Excess Load | Roof Leakages |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| 3 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 4 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| 5 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 |
| 6 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 8 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 9 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 10 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| 11 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 13 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| 14 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 15 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| 16 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 17 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| 18 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 19 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| 20 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . | . |
| 73 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |

The data collected from the 73 surveyed buildings were converted into a sparse numerical matrix to facilitate analysis, as the raw dataset was originally recorded in binary form (“yes” or “no”). In this matrix, a value of 0 denotes the absence of a particular defect cause (i.e., “no”), while a value of 1 indicates its presence (i.e., “yes”). For example, in Case 6, the absence of soil drainage, adequate landscaping, excessive wall load, and roof leakage was represented by 0. Conversely, 1 was assigned to observed defect causes such as root growth and drought in Case 1. This sparse matrix served as the input dataset for analysis in the RapidMiner software. Subsequently, the numerical data were converted to a binomial format using the Numerical to Binominal operator within RapidMiner to enable association rule mining and pattern recognition.

### Association Rules Generated

Association rules that satisfied the operational parameters defined for this research were generated using the Apriori algorithm. The parameters applied include a minimum support threshold of 0.5, a minimum confidence threshold of 0.6, and a maximum of three items for antecedents and consequents. All rules that did not meet these criteria were automatically excluded by the algorithm. The resulting association rules are presented in serial 1 – 9, while the significant associations are captured in Table 5.

1) [ROOF LEAKAGE] → [ LANSDCAPING] (confidence: 0.667)
2) [LANDSCAPING + DROUGH] → [ROOT GROWTH] (confidence: 0.667)
3) [ROOT GROWTH + ROOF LEAKAGE] → [LANSDCAPING] (confidence: 0.667)
4) [LANDSCAPING] → [ROOT GROWTH] (confidence: 0.756)
5) [PLUMBING] → [ROOT GROWTH] (confidence: 0.765)
6) [DROUGH] → [ROOT GROWTH] (confidence: 0.778)
7) [ROOF LEAKAGE] → [ROOT GROWTH] (confidence: 0.889)
8) [LANDSCAPING + ROOF LEAKAGE] → [ROOT GROWTH] (confidence: 0.889)
9) [DROUGHT + ROOF LEAKAGE] → [ROOT GROWTH] (confidence: 1.000)

Table 5: The association rules of causes of cracks in the buildings

| S/N | Premises | Conclusion | Support | Confidence | Lift |
|---|---|---|---|---|---|
| **1** | Landscaping | Root Growth | 0.466 | 0.756 | 0.935 |
| **2** | Plumbing | Root Growth | 0.178 | 0.765 | 0.946 |
| **3** | Drought | Root Growth | 0.384 | 0.778 | 0.962 |
| **4** | Roof Leakage | Root Growth | 0.329 | 0.889 | 1.100 |
| **5** | Landscaping, Roof Leakage | Root Growth | 0.219 | 0.889 | 1.100 |
| **6** | Drought, Roof Leakage | Root Growth | 0.178 | 1 | 1.237 |

Table 5 presents the association rules derived from the ARM analysis, showing the support, confidence, and lift values of the relationships that satisfy the Apriori algorithm. From the association rule analysis, the support, confidence, and lift values were obtained as summarized in Table 4. The study applied a minimum support threshold of 0.5, meaning that any rule with a support value below 50% was pruned from the dataset. Support is a critical measure in association rule mining, as rules with very low support may represent rare or statistically insignificant relationships. Therefore, to minimize the inclusion of uninformative associations, only rules meeting the minimum support criterion were retained.

The Table further shows that, the rule Landscaping → Root growth has a support value of 0.466, indicating that this relationship appears in 46.6% of the dataset. Plumbing → Root growth has a support of 0.178, appearing in 17.8% of the dataset, while Drought → Root growth has a support of 0.384, representing 38.4% of the data. Similarly, Roof leakage → Root growth shows a support of 0.329, occurring in 32.9% of the cases. The rule Landscaping → Roof leakage → Root growth has a support value of 0.219, signifying its presence in 21.9% of the cases, while Drought → Roof leakage → Root growth has a support of 0.178, appearing in 17.8% of the dataset.

A minimum confidence threshold of 0.6 (60%) was also employed to ensure that only reliable and consistent rules were considered. The confidence values of the generated rules are also presented in Table 5. The rule Landscaping → Root growth has a confidence of 0.756, meaning there is a 75.6% likelihood that root growth will occur when inadequate landscaping is present. Similarly, Plumbing → Root growth shows a confidence of 0.765, indicating a 76.5% likelihood that root growth will occur when plumbing issues exist. The rule Roof leakage → Root growth exhibits a confidence of 0.889, meaning there is 88.9% probability that root growth is associated with roof leakage. Likewise, Landscaping → Roof leakage → Root growth has a confidence of 0.889, suggesting that when both inadequate landscaping and roof leakage are present, root growth is also likely to occur.

Finally, Drought → Roof leakage → Root growth has a confidence value of 1.000, signifying a perfect confidence level – implying that whenever drought and roof leakage occur together, root growth is always observed.

The results further reveal that root growth contributes to 89% (0.889) of cases when associated with roof leaks, while drought conditions amplify crack formation by 78% (0.778). To mitigate these effects, it is essential to address minor leaks before environmental stressors, such as drought, exacerbate structural vulnerabilities. Particularly noteworthy is the triple interaction among drought, roof leakage, and root growth, which accounts for 17.8% of cases with perfect confidence – indicating a strong and consistent co-occurrence. These findings are consistent with prior research on tropical building pathology (Aljassmi & Han, 2013).

More so, the rule Landscaping → Root growth has a lift value of 0.935, suggesting an inverse correlation – meaning these factors occur together less frequently than expected under the assumption of conditional independence. Also, the rule Plumbing → Root growth has a lift value of 0.946, indicating that they appear as frequently as expected under the assumption of conditional independence (which means that they are independent of each other). Similarly, the rule Drought → Root growth has a lift value 0.962, also indicating that they appear as frequently as expected under the assumption of conditional independence (which means that they are independent of each other). Conversely, Roof leakage → Root growth has a lift value of 1.100, showing a positive correlation, i.e., they occur together more frequently than expected. Likewise, Landscaping → Roof leakage → Root growth also exhibits a lift value of 1.100, indicating positive interdependence. Finally, Drought → Roof leakage → Root growth has the highest lift value of 1.237, representing the strongest positive association among all identified rules. The ARM analysis yielded significant interrelationships. The strongest associations are shown in serial (1-3).

1. Drought + Roof Leakage → Root Growth (Support=0.178, Confidence=1.000, Lift=1.237)
2. Roof Leakage → Root Growth (Support=0.329, Confidence=0.889, Lift=1.100)
3. Landscaping → Root Growth (Support=0.466, Confidence=0.756, Lift=0.935)

From the above, associations (serial 1-3), root growth appears to be the most significant factor both in the singular cause analysis and the ARM analysis (appear in all the three strongest associations). However, inadequate landscaping and drought appear to be among the top factors in the singular cause analysis but appear only in one of the strongest associations each in the ARM analysis. This result confirms that when drought and roof leakage occur simultaneously, there is a very high probability that trees have been planted too close to the buildings, resulting in root-induced structural damage. In other words, buildings experiencing drought-related stress and roof leakage are highly likely to exhibit defects caused by nearby tree roots. This also suggests that the presence of trees close to the buildings may exacerbate roof leakages, possibly due to the mechanical and physical effects of overhanging branches and leaf accumulation on roofs. Additionally, tree roots may intensify drought conditions around the building foundations by absorbing significant amounts of soil moisture, further contributing to structural distress. The outcome of this research could be supported by Mclean (2009) and Li and Guo (2016) who found out that the influence of tree roots and moisture content cause localized shrinkage and differential settlements near foundations leading to cracks. Additionally, the result aligns with that of Murphy (2020) and Houston et al. (2011) who found out poor landscaping to be among the significant factors causing cracks. Contrary to these results, Gurmu et al., (2020), found out that inadequate landscaping appears to be among the less significant factors causing cracks.

Figure 1 shows the association rules network graph indicating the association of the factors causing cracks. This illustrates the complex interactions between primary crack causes. This shows that crack formation results from factor combinations rather than isolated causes as in the case of the singular cause analysis.

Figure 2 also shows the directional relationships between defect causes, with edge color and thickness proportional to confidence values. In the context of this research, the ARM approach has successfully quantified hidden relationships that traditional statistical methods might overlook.

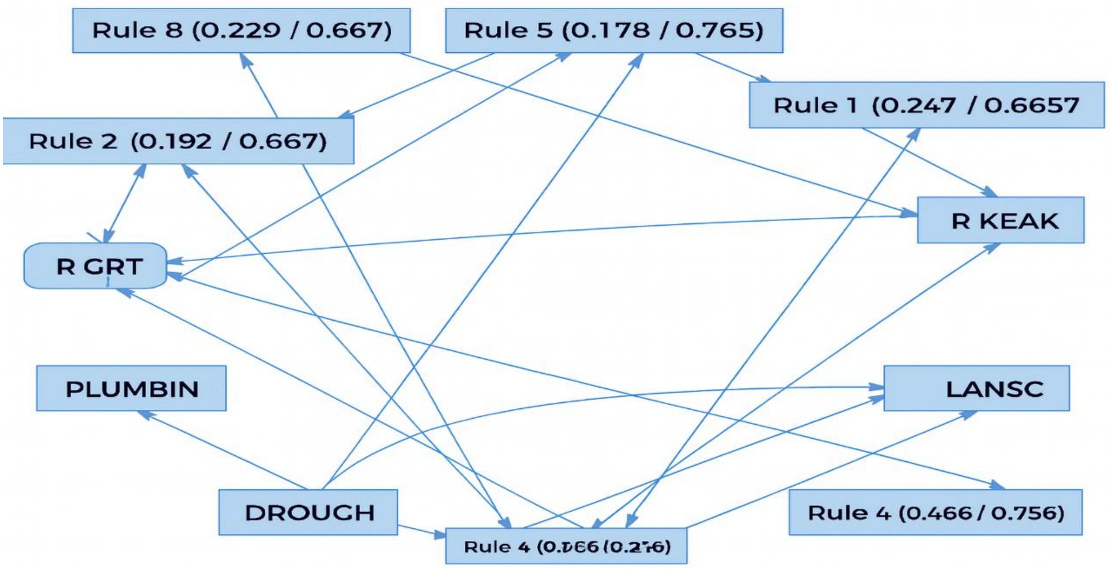


**Figure 1: Association rules network graph**

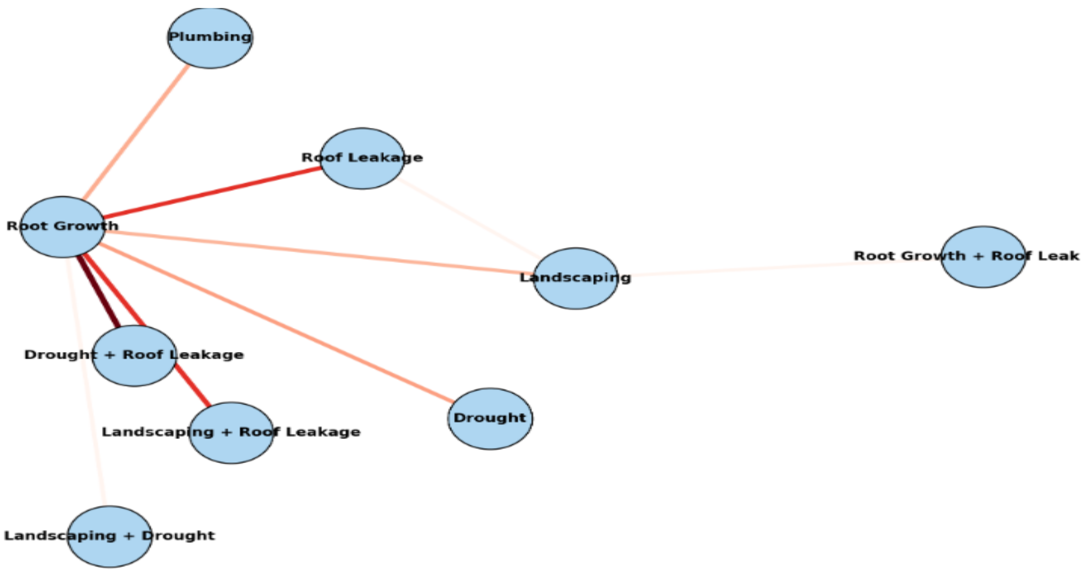


**Figure 2: Association network of defect-related factors**

## CONCLUSION AND RECOMMENDATION

### Conclusion

This study evaluated the single cause and the interrelationships among the factors causing cracks in buildings in order to identify the most significant relationships amongst the causes of crack in residential buildings. The study concluded that root growth, inadequate landscaping and drought to be the most frequent causes of cracks based on the single cause analysis. ARM revealed strong associations, particularly between root growth and the combined effects of drought and roof leakage, indicating synergistic interactions. Root growth appears to be the most prevalent factors causing cracks, exacerbated by drought and roof leakage. Poor landscaping contributed to moisture accumulation, aggravating crack formation. ARM effectively identified hidden relationships by highlighting the interconnected nature of crack causes, with root growth, drought, and roof leakage exhibiting the strongest association.

### Recommendation

It is recommended that trees should be planted at a safe distance from buildings to prevent root-related damage. Also, proper grading and drainage should be ensured to avoid moisture accumulation. More so, regular inspection of roofs and plumbing should be carried out to prevent leaks. Future research could expand the dataset to include more diverse building types and climates. The study limitations are that, it focused on a single location which could hinder generalizability of the research findings to other locations. More so, crack measurements were only taken for the external walls of the residential buildings as such, crack assessments do not comprehensively cover the internal walls of the residential buildings. Future research could therefore be conducted to address the limitations of the current study.

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