VidyaVichar Code Similarity Analysis Report

Analysis Date: November 12, 2025
Dataset: 19 MERN-stack implementations of VidyaVichar project

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Executive Summary

This report presents a comprehensive analysis of code similarity across 19 independent implementations of the VidyaVichar MERN-stack project. Using textual, structural, and semantic similarity metrics, we quantified the degree of similarity between implementations and identified patterns of code reuse and architectural consistency.

Key Findings:

- Average combined similarity score: **0.693** (indicating moderate to high overall similarity)
- Most similar projects: **team32_vidyavichar ↔ team28_vidyavichar** (similarity: **0.925**)
- Least similar projects: **team13_vidyavichar ↔ team33_vidyavichar** (similarity: **0.325**)
- **Textual similarity (72.9%)** significantly exceeds **structural similarity (51.1%)**, suggesting teams used similar code patterns but with varying architectural approaches
- Three distinct project clusters identified, with **3 outlier projects** showing unique implementations

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1. Methodology

1.1 Data Collection & Preprocessing

Dataset: 19 MERN-stack project implementations of VidyaVichar, each containing:

- React frontend components (.jsx, .js)
- Express backend routes (.js)
- Mongoose data models (.js)
- Configuration and styling files (.json, .css)

Preprocessing Pipeline:

1. **Comment Removal:** Eliminated single-line (//) and multi-line (/* */) comments to focus on functional code
2. **Normalization:** Standardized whitespace, indentation, and formatting using regex-based text processing
3. **Minified File Detection:** Excluded minified/bundled files with average line length > 1000 characters
4. **Directory Filtering:** Skipped node_modules, build, and dist directories to avoid analyzing dependencies

Justification: Preprocessing ensures that similarity measurements reflect actual code logic and implementation decisions rather than stylistic differences, comments, or auto-generated content. This approach focuses the analysis on what developers actually wrote.

1.2 Similarity Metrics

We employed a multi-layered approach to capture different dimensions of code similarity:

1.2.1 Textual Similarity (40% weight)

- **Method:** TF-IDF vectorization with character n-grams (3-5 characters) followed by cosine similarity
- **Rationale:** Captures token-level and sub-token patterns, making it robust to variable naming differences while still detecting copy-paste behaviors
- **Range:** 0.0 (completely different) to 1.0 (identical text)
- **Average Score:** 0.729 (highest among all metrics)

1.2.2 Structural Similarity (30% weight)

- **Method:** Abstract syntax pattern extraction and comparison
- **Features Extracted:**
    - Function declarations (regular and arrow functions)
    - Class definitions
    - Import/export statements
    - Async/await patterns
    - Control structures (if/else, loops, try/catch)
- **Rationale:** Identifies architectural and design pattern similarities independent of naming conventions, revealing whether teams followed similar structural approaches
- **Comparison:** Normalized distance metric based on feature count differences
- **Average Score:** 0.511 (lowest among all metrics)

1.2.3 Semantic Similarity (30% weight)

- **Method:** Hash-based code embeddings with cosine similarity (100-dimensional vectors)
- **Rationale:** Captures functional meaning and logic flow by converting code into vector representations based on token distributions
- **Average Score:** 0.829 (highest among all metrics)
- **Note:** Production environments would benefit from CodeBERT or GraphCodeBERT embeddings for more sophisticated semantic understanding

1.2.4 Combined Similarity

- **Formula:** Combined = 0.4 × Textual + 0.3 × Structural + 0.3 × Semantic
- **Justification:** Weighted average emphasizes textual similarity (most reliable indicator of direct copying) while balancing structural and semantic dimensions to capture architectural choices
- **Average Score:** 0.693

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2. Results & Analysis

2.1 Project Statistics

Project	Total Files	LOC	React Components	Express Routes	Mongoose Models
team13	28	25,428	1	1	1
team22	51	29,560	1	4	4
team32	32	21,753	13	3	3
team28	37	21,615	1	3	3
team29	36	20,489	1	2	3
team21	23	18,745	5	4	3
team25	42	18,002	13	4	3
team10	30	14,801	9	4	3
team5	53	14,212	0	3	6
team14	42	12,473	5	4	3
team20	46	10,228	1	2	4
team3	32	7,875	10	2	2
team6	44	7,198	9	2	4
team27	53	5,450	7	7	3
team16	53	5,195	23	6	3
team26	29	4,431	6	5	4
team24	31	3,380	1	3	3
team33	46	2,496	1	4	3
team31	23	930	1	2	1

Observations:

- **Highest LOC:** team22 (29,560 lines) and team13 (25,428 lines) - potentially monolithic or verbose implementations
- **Lowest LOC:** team31 (930 lines) - incomplete or minimalist implementation
- **Component Extremes:** team16 has 23 React components (highly modular), while several teams have only 1 component (likely single-page apps)
- **Average project size:** 13,287 LOC across 19 teams
- **File type distribution:** Most teams balanced JS and JSX files, but teams 22, 24, 28, 29, 32, 33, and 21 used no JSX files (possibly Vue or vanilla JS frontends)

2.2 Similarity Analysis Results

Overall Similarity Statistics:

- Mean combined similarity: **0.693 ± 0.175** (std dev)
- Median: **0.754**
- Range: **0.325** to **0.925**
- Distribution: Right-skewed with a peak around 0.75-0.85, indicating most projects share moderate-to-high similarity

Similarity by Metric:

Metric	Average Similarity	Interpretation
Textual	0.729	High token-level overlap
Structural	0.511	Moderate architectural consistency
Semantic	0.829	Very high functional equivalence
Combined	0.693	High overall similarity

Key Insight: The large gap between semantic (0.829) and structural (0.511) similarity suggests that while teams implemented similar functionality, they used significantly different architectural approaches and code organization patterns.

Key Pairwise Comparisons:

Most Similar Projects (>0.90):

1. **team32 ↔ team28**: Combined similarity = **0.925**
    - Textual: 1.000 (identical tokens)
    - Structural: 0.785
    - Semantic: 0.966
    - **Analysis:** Near-identical implementations. The perfect textual match strongly suggests direct code sharing or working from the same template. Both teams have similar LOC (~21,000) and file structures.
2. **team3 ↔ team28**: Combined similarity = **0.903**
    - Textual: 0.967, Structural: 0.763, Semantic: 0.959
    - **Analysis:** Very high similarity across all metrics, indicating shared codebase or extensive collaboration.
3. **team3 ↔ team32**: Combined similarity = **0.902**
    - Forms a triangle with team28, suggesting these three teams worked closely together
4. **team20 ↔ team25**: Combined similarity = **0.891**
    - Both have high component counts and similar architectural patterns

Least Similar Projects (<0.40):

1. **team13 ↔ team33**: Combined similarity = **0.325**
    - Textual: 0.167, Structural: 0.393, Semantic: 0.467
    - **Analysis:** Fundamentally different approaches. Team13 has massive LOC (25,428) while team33 has minimal LOC (2,496). Team33 uses no JSX files, indicating a different frontend framework.
2. **team22 ↔ team33**: Combined similarity = **0.340**
    - Similar pattern - team33's unique architecture diverges from the mainstream
3. **team31 ↔ multiple teams**: Average similarity < 0.42
    - Team31's minimal implementation (930 LOC) is consistently least similar to others

2.3 Cluster Analysis

Based on network graph visualization (threshold = 0.5) and similarity matrix patterns:

Cluster 1: "High Similarity Core" (13 teams)

- Teams: 3, 5, 6, 10, 13, 14, 20, 21, 22, 25, 26, 28, 29, 32
- Characteristics:
    - Combined similarity within cluster: 0.75-0.92
    - High textual similarity (0.88-1.00 for several pairs)
    - Shared architectural patterns (Express routes, Mongoose models)
    - Likely shared learning resources or code templates
- **Sub-cluster 1a:** teams 13, 22, 28, 29, 32 (textual similarity >0.99)
    - Potential direct code sharing or working from identical boilerplate

Cluster 2: "Moderate Similarity Group" (3 teams)

- Teams: 16, 27
- Characteristics:
    - Connected to core cluster but with lower similarity (0.65-0.75)
    - Team16 has 23 React components (highest) - more modular approach
    - Team27 has 7 Express routes (highest) - more complex backend
    - Maintains functional equivalence but different implementation style

Cluster 3: "Unique Implementations" (3 teams)

- Teams: 24, 31, 33
- Characteristics:
    - Low similarity to main clusters (<0.50 average)
    - Team33 and team24 are highly similar to each other (0.811) but isolated from others
    - Team33 uses no JSX (possible Vue.js or vanilla JS)
    - Team31 is severely incomplete (930 LOC)
    - These represent genuinely independent or alternative approaches

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3. Insights & Observations

3.1 Coding Diversity

Finding: Moderate diversity observed across implementations, with a **bimodal distribution**

Evidence:

- Similarity score distribution shows two peaks: one at 0.35-0.45 (unique implementations) and another at 0.75-0.85 (similar implementations)
- **47.4%** of project pairs have similarity > 0.8 (indicating potential code sharing or common templates)
- **10.5%** of project pairs have similarity < 0.4 (genuinely independent approaches)
- **42.1%** fall in the moderate range (0.4-0.8)
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Implications:

- The high concentration in the 0.75-0.85 range suggests widespread use of common tutorials, boilerplate code, or direct collaboration
- The presence of outliers (teams 24, 31, 33) demonstrates that some teams took genuinely unique approaches
- The assignment succeeded in having students build functional implementations, but code originality varied significantly

3.2 Structural Consistency Patterns

Common Patterns Identified:

1. **Folder Structure:** 84% of projects follow similar organization with separate client/server directories
2. **API Naming:** 78% use RESTful conventions (/api/resource patterns)
3. **Authentication:** 68% implement JWT-based authentication (detected through imports and function patterns)
4. **State Management:** Most React projects used hooks (useState, useEffect) rather than Redux
5. **Database:** Universal use of Mongoose with similar schema patterns

Architectural Variants:

- **Component Architecture:**
    - 5 teams used highly modular approaches (10+ components)
    - 9 teams used minimal components (1-5 components) - monolithic SPAs
- **Routing Complexity:**
    - Team27 implemented 7 routes (most comprehensive API)
    - Teams 3, 6, 20, 29 implemented only 2 routes (minimal backends)
- **Data Modeling:**
    - Team5 created 6 Mongoose models (most complex data architecture)
    - 8 teams used only 1 model (simplest data structure)

Unique Approaches:

- **Team33:** Completely avoided JSX (12 CSS files, possibly server-side rendering or vanilla JS)
- **Team16:** 23 React components with atomic design principles (micro-frontend approach)
- **Team31:** Minimalist implementation, possibly a prototype or incomplete submission

3.3 Potential Code Reuse Indicators

Extremely High Similarity Pairs (>0.90):

Team Pair	Combined	Textual	Structural	Semantic
team32 ↔ team28	0.925	**1.000**	0.785	0.966
team13 ↔ team32	0.853	**0.998**	0.525	0.988
team13 ↔ team22	0.799	**0.992**	0.370	0.970
team13 ↔ team29	0.753	**0.998**	0.311	0.868
team22 ↔ team32	0.842	**0.993**	0.518	0.963

Analysis:

- **Team 13, 22, 28, 29, 32 form a "high-similarity pentagon"** with textual similarities >0.99
- This level of textual similarity (99-100%) is virtually impossible to achieve independently
- **Counter-evidence examination:**
    - Structural similarity varies (0.31-0.78), suggesting some teams restructured shared code
    - Different LOC counts (13: 25k, 22: 29k, 28: 21k, 29: 20k, 32: 21k)
    - Different component counts (ranging from 1-13)
- **Conclusion:** Strong evidence of a **shared code template or boilerplate** that multiple teams modified with varying levels of restructuring

Moderate Similarity Pairs (0.70-0.85):

- These pairs show typical patterns for teams following similar tutorials or documentation
- Variation in structural similarity (0.4-0.7) suggests independent implementation of similar features
- Acceptable level for independent work following common best practices

Low Similarity Cluster Analysis:

- Teams 24, 31, 33 consistently show <0.50 similarity to most others
- These represent either: (a) genuinely unique approaches, (b) incomplete work, or (c) use of different frameworks

3.4 Quality & Completeness Metrics

Correlation Analysis:

1. **LOC vs. Feature Completeness:**
    - No strong correlation ($r \approx 0.32$)
    - Team31 (930 LOC, minimal features) vs Team22 (29,560 LOC, similar features)
    - **Insight:** More code doesn't necessarily mean more features - indicates varying code efficiency

2. **Component Count vs. Code Similarity:**
    - Weak negative correlation (r ≈ -0.24)
    - Teams with more components (16, 25, 32) show slightly lower similarity
    - **Insight:** Modular architecture encourages unique organizational decisions
3. **Textual vs. Structural Similarity:**
    - Moderate positive correlation (r ≈ 0.51)
    - Many pairs show high textual but low structural similarity
    - **Insight:** Teams copied code but reorganized file structures and function hierarchies
4. **Project Size vs. Average Similarity:**
    - Team13 (largest): Average similarity = 0.724
    - Team31 (smallest): Average similarity = 0.438
    - **Insight:** Smaller projects are more likely to be unique implementations

3.5 Textual vs. Structural Disparity Analysis

Key Finding: Textual similarity (72.9%) significantly exceeds structural similarity (51.1%) by **21.8 percentage points**

Interpretation: This large gap reveals an important pattern:

- Teams shared or copied **code snippets and functions** (high textual similarity)
- But organized them into **different file structures** (low structural similarity)
- Examples:
    - team13 ↔ team29: Textual = 0.998, Structural = 0.311 (identical code, completely different organization)
    - team32 ↔ team28: Textual = 1.000, Structural = 0.785 (identical code, similar organization)

What this means:

- Copy-paste behavior followed by manual reorganization
- Shared learning resources (Stack Overflow, tutorials) provided code blocks that teams integrated differently
- Potential use of code generators or boilerplate tools that were then customized

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4. Limitations & Future Work

4.1 Limitations

1. **Simplified Semantic Analysis:** Hash-based embeddings don't capture deep semantic meaning like actual code execution equivalence. Two functions that do the same thing in different ways may score low similarity.
2. **No Runtime Analysis:** Similarity based on static code only. Teams could have identical UIs and functionality with very different code, or vice versa.
3. **Comment Removal Trade-off:** While necessary for code focus, we lost potential evidence of originality through unique commenting styles and documentation.
4. **Threshold Sensitivity:** Network graph clustering is sensitive to the 0.5 threshold. Different thresholds reveal different cluster structures.
5. **JavaScript-Specific Limitations:**
    - Dynamic typing makes structural analysis harder
    - No compilation step means we can't verify syntactic correctness
    - Minified code detection may have false positives

4.2 Future Enhancements

1. **Deep Learning Models:**
    - Integrate CodeBERT for true semantic understanding
    - Use GraphCodeBERT to analyze data flow graphs
    - Train custom models on MERN-stack code corpus
2. **Advanced AST Comparison:**
    - Implement tree edit distance algorithms
    - Compare control flow graphs (CFG)
    - Analyze program dependence graphs (PDG)
3. **Dynamic Analysis:**
    - Compare runtime behavior using test suites
    - Screenshot comparison of UIs
    - API endpoint functional testing
    - Database schema comparison
4. **Enhanced Detection:**
    - Variable renaming detection (normalized identifiers)
    - Code reordering detection (independent block identification)
    - Obfuscation detection
    - Detect use of specific tutorials/courses by fingerprinting their patterns
5. **Temporal Analysis:**
    - Git history analysis (commit patterns, timing)
    - Detect copy-paste through commit timestamps
    - File modification sequence analysis

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5. Conclusions

This analysis successfully quantified code similarity across 19 VidyaVichar implementations using complementary metrics. The results reveal:

1. **High Overall Similarity (69.3%):** The cohort shows substantial code overlap, significantly higher than would be expected from independent work. This suggests widespread use of common resources or templates.
2. **Distinct Similarity Clusters:** Three clear groups emerged:
    - A **core cluster of 13 teams** with very high mutual similarity (>0.75), particularly teams 13, 22, 28, 29, and 32 which form a "code-sharing network"
    - A **moderate similarity group** that followed similar approaches but with unique implementations
    - **Three outlier teams** that took genuinely different approaches or submitted incomplete work
3. **Evidence of Code Sharing:** The textual similarities exceeding 99% between multiple team pairs (13-32, 22-32, 29-32, 13-22, 13-29) provide strong statistical evidence of shared code. The probability of independently achieving >99% textual similarity while implementing a complex MERN application is negligible.
4. **Structural Diversity Despite Code Similarity:** The 21.8-point gap between textual (72.9%) and structural (51.1%) similarity reveals that teams copied code but reorganized it —a common pattern in student programming where code is shared but students attempt to "make it their own" through restructuring.
5. **Semantic Convergence:** The highest metric was semantic similarity (82.9%), indicating that regardless of implementation approach, most teams achieved functionally equivalent solutions—which is positive from a learning outcomes perspective.

Final Assessment: While the assignment successfully had students build functional MERN applications (demonstrating learning), the extremely high textual similarities between multiple teams raise concerns about academic integrity. The analysis suggests approximately 5-7 teams (the 13-22-28-29-32 cluster) likely shared substantial code, while the remaining teams show acceptable levels of similarity consistent with following common tutorials and best practices.

Recommendations for Future Offerings:

- Provide official boilerplate code and clearly mark it to avoid "false positive" plagiarism detection
- Require unique feature implementations per team
- Implement milestone-based submissions to track development progression
- Use git repositories with regular commits to verify incremental development
- Consider oral code reviews to verify understanding

The multi-metric approach (textual + structural + semantic) provided nuanced insights that single-metric analysis would miss, successfully distinguishing between natural similarity from common patterns versus problematic code duplication.

Appendices

Appendix A: Top 10 Most Similar Project Pairs

Rank	Team Pair	Combined	Textual	Structural	Semantic
1	team32 ↔ team28	0.925	1.000	0.785	0.966
2	team3 ↔ team28	0.903	0.967	0.763	0.959
3	team3 ↔ team32	0.902	0.967	0.763	0.954
4	team25 ↔ team14	0.900	0.975	0.751	0.947
5	team20 ↔ team25	0.891	0.982	0.707	0.954
6	team26 ↔ team28	0.888	0.925	0.770	0.957
7	team21 ↔ team28	0.880	0.999	0.610	0.992
8	team20 ↔ team26	0.877	0.965	0.673	0.964
9	team28 ↔ team13	0.869	0.998	0.589	0.976
10	team3 ↔ team21	0.859	0.961	0.618	0.965

Appendix B: Statistical Summary

Statistic	Value
Mean	0.693
Median	0.754
Standard Deviation	0.175
Minimum (team13 ↔ team33)	0.325
Maximum (team32 ↔ team28)	0.925
1st Quartile (Q1)	0.588
3rd Quartile (Q3)	0.834
