EntropyX: PE Feature Extractor for Malware Classification

> **Project Goal:** Build a robust feature extractor for Malware Classification using Random Forest.
> **Last Updated:** February 2026

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1. Project Overview

This project extracts features from Portable Executable (PE) files to train a machine learning model that distinguishes **malware** from **benign** executables. The primary signal is **Shannon Entropy**, which measures randomness in data—encrypted or compressed malware payloads have distinctively high entropy.

Key Files

File	Purpose
`extractor.py`	Main feature extraction logic
`builder.py`	Batch processes PE files → generates dataset.csv
`trainer.py`	Trains Random Forest model & evaluates results

File	Purpose
`generate_custom_malware.sh`	Creates synthetic high-entropy malware samples
`generate_benign.sh`	Retrieves legitimate Windows system files
`data/malicious/`	Training samples (custom loaders + SGN encoded)
`data/benign/`	Legitimate Windows executables

2. The Problem & Why Entropy Matters

Initial Hypothesis (Flawed)

> "Simply calculate the entropy of the whole file to detect malware."

Why It Failed

Issue	Explanation
False Positives	Benign installers (e.g., `.msi`, compressed apps) also have high entropy
Missed Detections	Malware hides encrypted payloads in *small sections*, while the rest is null padding—averaging the whole file dilutes the signal
Example	`custom_loader.exe` showed only **1.4 entropy** at file-level, but **7.13 entropy** in its `.data` section

The Solution

Section-Aware Analysis — Analyze each PE section individually, then summarize with statistics.

3. Development Timeline (Git Commit History)

This section maps each commit to the problem it solved and the performance/accuracy improvement gained.

Commit 1: `1fbe40a` — Scripts to generate or retrieve training

data

What: Created shell scripts to automate dataset generation.

Why: Manual data collection doesn't scale. Needed 600+ samples for balanced training.

Commit 2: `c843e16` — Wrote the function to calculate Shannon entropy

What: First implementation of `shanon_helper()` .

```
# BEFORE (Naive approach)
probabilities = {byte: count / total_bytes for byte, count in counter.items()}
for prob in probabilities.values():
    entropy += prob * math.log2(prob)
entropy = 0.0 - entropy  # Negation at the end
```

Problem: Created an intermediate dictionary (`probabilities`) unnecessarily—wasted memory on large files.

Commit 3: `7b2fe64` — Optimized the `shanon_helper` function

What: Eliminated the intermediate dictionary and added safety checks.

```
# AFTER (Optimized)
for count in counter.values():
    prob = count / total_bytes
    entropy -= prob * math.log2(prob)  # Direct subtraction
```

Improvement	Before	After
Memory allocation	Dict of 256 entries	None (direct iteration)
Empty file handling	❌ Division by zero crash	✅ Returns 0.0 safely
Readability	Two-step (calculate, then negate)	One-step (subtract directly)

Commit 4: `1b71e0c` — Updated `extractor.py` and `generate_custom_malware.sh`

What: Two critical changes.

Change A: Refactored `shanon_helper` to accept binary data (not file path)

```
# BEFORE: Tightly coupled to file I/O
def shanon_helper(filepath):
    with open(filepath, 'rb') as file:
        file_bytes = file.read()

# AFTER: Pure function, accepts any bytes
def shanon_helper(binary_data):
    counter.update(binary_data)
```

Improvement	Impact
Testability	Can now unit test with `b'\x00\xff'` without creating files
Reusability	Same function works for PE sections, raw buffers, network streams
Performance	Avoids redundant file opens when PE is already parsed

Change B: Fixed the "Hex Trap" in malware generation

The Bug: Generating payloads as hex strings (`A-F0-9`) limited entropy to ~**4.0 bits**.

> Hex uses only 16 characters (4 bits of entropy max), not 256 possible byte values (8 bits).

```
# BEFORE (Limited entropy)
PAYLOAD_DATA=$(head /dev/urandom | tr -dc A-F0-9 | head -c $PAYLOAD_SIZE)
const char encrypted_payload[] = "$PAYLOAD_DATA";  # Stored as ASCII string

# AFTER (True randomness)
PAYLOAD_ARRAY=$(head -c $PAYLOAD_SIZE /dev/urandom | od -An -v -t x1 | ...)
unsigned char encrypted_payload[] = { $PAYLOAD_ARRAY };  # Stored as raw bytes
```

Metric	Before (Hex String)	After (Raw Bytes)
Max theoretical entropy	4.0 bits	8.0 bits

Metric	Before (Hex String)	After (Raw Bytes)
Actual measured entropy	~3.8 bits	~7.99 bits
Realism	❌ No real malware uses hex	✅ Mimics AES/RC4 encrypted payloads

Commit 5: `a1dd06c` — Orchestrator v1 and `get_structural_features`

What: Introduced the Orchestrator pattern and added structural features.

New Features Extracted

Feature	Why It Matters
`num_sections`	Packed malware often has unusual section counts
`virtual_size_ratio`	Ratio > 1.0 indicates runtime unpacking (malware signal)
`raw_size` vs `virtual_size`	Discrepancy reveals hidden payloads

Architectural Change: Orchestrator Pattern

```
def extract_all_features(filepath) -> dict:  # Orchestrator
    pe = pefile.PE(filepath)
    features = {}
    features.update(get_entropy_features(pe))      # Worker 1
    features.update(get_structural_features(pe))   # Worker 2
    pe.close()
    return features
```

Benefit	Explanation
Extensibility	Add `get_import_features()` without touching entropy logic
Single Responsibility	Each worker does one thing well
Resource Safety	`pe.close()` in one place (now in `finally` block)

Commit 6: `builder.py` — Dataset CSV Generator (Bug Fixes)

What: Created `builder.py` to batch-process all PE files and generate a training CSV.

⚠️ Bug A: `os.walk` Yields a Tuple, Not a File Path

The Mistake:

```
for file in os.walk('../data/benign', topdown=True):
    row = extract_all_features(file)  # ❌ CRASH: passing a tuple!
```

What Happened:

`os.walk()` doesn't yield file paths—it yields a **3-tuple**: `(current_folder, list_of_subfolders, list_of_files)`. The code passed the entire tuple to `pefile.PE()`, which expects a string path.

The Fix:

```
for root, dirs, files in os.walk('../data/benign'):  # ✅ Unpack the tuple
    for filename in files:
        full_path = os.path.join(root, filename)     # ✅ Reconstruct full path
        row = extract_all_features(full_path)
```

Component	What It Contains	Example
`root`	Current directory path	`../data/benign/subdir`
`dirs`	List of subdirectory names	`['folder1', 'folder2']`
`files`	List of file names (no path!)	`['file1.exe', 'file2.dll']`

⚠️ Bug B: Memory Trap — Accumulating All Rows Before Writing

The Mistake:

```
rows = []
for root, dirs, files in os.walk('../data'):
    for filename in files:
        row = extract_all_features(...)
        rows.append(row)  # ❌ Stores everything in RAM

# Write all at once at the end
writer.writerows(rows)
```

The Problem:
At small scale (600 files), this works. At production scale (1 million files), storing 1 million dictionaries in RAM before writing a single line causes **memory exhaustion**.

The Fix — Streaming Pattern:

```
with open('dataset.csv', 'w') as csvfile:
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)
    writer.writeheader()

    for root, dirs, files in os.walk('../data'):
        for filename in files:
            row = extract_all_features(...)
            if row:
                writer.writerow(row)  # ✅ Write immediately, then discard
```

Approach	Memory Usage (1M files)	Disk I/O
Accumulate then write	~8GB+ (crash likely)	One burst at end
Stream (write immediately)	~constant (~1KB)	Continuous, efficient

Lesson Learned:
Never accumulate unbounded data in memory. Write/process incrementally ("streaming") to keep RAM usage constant regardless of input size.

⚠️ Bug C: Missing File Extension Filter

The Mistake:

```
for filename in files:
    row = extract_all_features(os.path.join(root, filename))
    # ❌ Will try to parse .sh, .DS_Store, .txt, etc.
```

The Problem:
The data directory might contain non-PE files (shell scripts, macOS metadata, logs). Attempting to parse them with `pefile` causes unnecessary errors and clutters logs.

The Fix:

```
for filename in files:
    if filename.endswith(('.exe', '.dll')):  # ✅ Filter before processing
        row = extract_all_features(os.path.join(root, filename))
```

File Type	Before (No Filter)	After (With Filter)
`malware.exe`	✅ Processed	✅ Processed
`generate.sh`	❌ Error logged	⏭️ Skipped silently
`.DS_Store`	❌ Error logged	⏭️ Skipped silently

Best Practice:
Always validate input before processing. Filtering early ("fail fast") prevents wasted computation and keeps logs clean.

4. Key Technical Decisions

Decision 1: VirtualSize vs. RawSize for Entropy Calculation

Observation: Malware often has `VirtualSize > SizeOfRawData` because it unpacks at runtime.

Problem: `section.get_data()` returns raw bytes padded with nulls, diluting entropy.

Solution:

```
section_data_trimmed = section.get_data()[:section.Misc_VirtualSize]
```

Scenario	Without Trimming	With Trimming

Scenario	Without Trimming	With Trimming
10KB encrypted payload + 90KB null padding	~0.8 entropy	~7.9 entropy

Decision 2: Statistical Aggregation for Variable-Length Data

Problem: ML models need fixed-length input vectors, but PE files have 3-10+ sections.

Solution: Summarize with statistical moments:

```
entropy_summary = {
    'avg_entropy': mean(entropies),    # Overall complexity
    'max_entropy': max(entropies),     # THE KEY SIGNAL (encrypted section)
    'min_entropy': min(entropies),     # Null-padded sections
    'std_entropy': np.std(entropies)   # Variance between sections
}
```

Why `std_entropy` is crucial:
Benign files have *consistent* entropy across sections. Malware has *spikes* (encrypted payload vs. empty padding). Standard deviation captures this variance.

Decision 3: Error Handling at Orchestrator Level

Pattern: Workers assume valid input; Orchestrator handles exceptions.

⚠️ Bug Discovered: UnboundLocalError in `finally` Block

The Mistake:

```
def extract_all_features(filepath) -> dict:
    try:
        pe = pefile.PE(filepath)  # If this fails, pe is never assigned
        # ... call workers ...
    except pefile.PEFormatError as e:
        print(f"Error processing {filepath}: {e}")
        return None
    finally:
        pe.close()  # ❌ CRASH: UnboundLocalError if file doesn't exist
```

What Happened:
When a `FileNotFoundError` occurred (wrong file path), the `pe = pefile.PE(filepath)` line threw an exception *before* `pe` was assigned. The `finally` block still executed, but `pe` didn't exist—causing a *second* error that masked the real problem.

The Fix:

```
def extract_all_features(filepath) -> dict:
    pe = None  # ✅ Initialize before try block
    try:
        pe = pefile.PE(filepath)
        # ... call workers ...
    except pefile.PEFormatError as e:
        print(f"Error processing {filepath}: {e}")
        return None
    finally:
        if pe is not None:  # ✅ Guard before closing
            pe.close()
```

Issue	Before	After
Missing file	`UnboundLocalError` masks real error	Shows actual `FileNotFoundError`
Invalid PE	`UnboundLocalError`	Graceful `None` return
Valid PE	Works	Works

Lesson Learned:
Always initialize resources to `None` before a `try` block when using `finally` for cleanup. This pattern is called **"Initialize-Try-Finally"** and prevents cascading errors.

Benefit	Impact
Cleaner workers	No redundant try/except in every function
Consistent error format	All errors logged the same way
Memory safety	`finally` ensures handles are closed even on crash
Error transparency	Real exceptions aren't masked by cleanup failures

5. Pythonic Implementation Details

5.1 Counter.update() vs. Manual Loop

```
# ❌ WRONG: Treats entire bytes object as one key
counter[file_bytes] += 1  # Result: Counter({b'...': 1})

# ❌ SLOW: Correct but inefficient
for byte in file_bytes:
    counter[byte] += 1

# ✅ OPTIMAL: C-optimized iteration
counter.update(file_bytes)  # ~10x faster for large files
```

Why `update()` is faster: Implemented in CPython's C internals, avoiding Python's interpreter overhead per byte.

5.2 Binary Data Representation in Python

Misconception: Expecting `b'\x7f\x45\x4c\x46'` when printing bytes.

Reality: Python displays printable ASCII: `b'\x7fELF'`

Insight: Internally, Python treats bytes as integers 0-255. To see them:

```
>>> list(b'ELF')
[69, 76, 70]
```

This is exactly what Shannon entropy math uses—256 possible byte values.

6. Architecture & Code Organization

```
extractor.py
├── shanon_helper(binary_data)       # Pure function: bytes → entropy float
├── get_entropy_features(pe)         # Worker: PE → entropy dict
├── get_structural_features(pe)      # Worker: PE → structure dict
└── extract_all_features(filepath)  # Orchestrator: path → final feature dict
```

Design Principles Applied

Principle	Implementation
Single Responsibility	Each function does exactly one thing
Dependency Injection	Workers receive `pe` object, don't open files
Fail Fast	Orchestrator validates PE before calling workers
Resource Management	`try/finally` ensures `pe.close()` always runs

7. Model Training & Results

7.1 Training Pipeline (`trainer.py` v1)

```
# Load and prepare data
df = pd.read_csv('../data/dataset.csv')

# Drop multicollinear and non-predictive features
X = df.drop(columns=['is_malicious', 'raw_size', 'virtual_size', 'filename'])
y = df['is_malicious']

# Stratified split (maintains class balance in train/test)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Train Random Forest
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

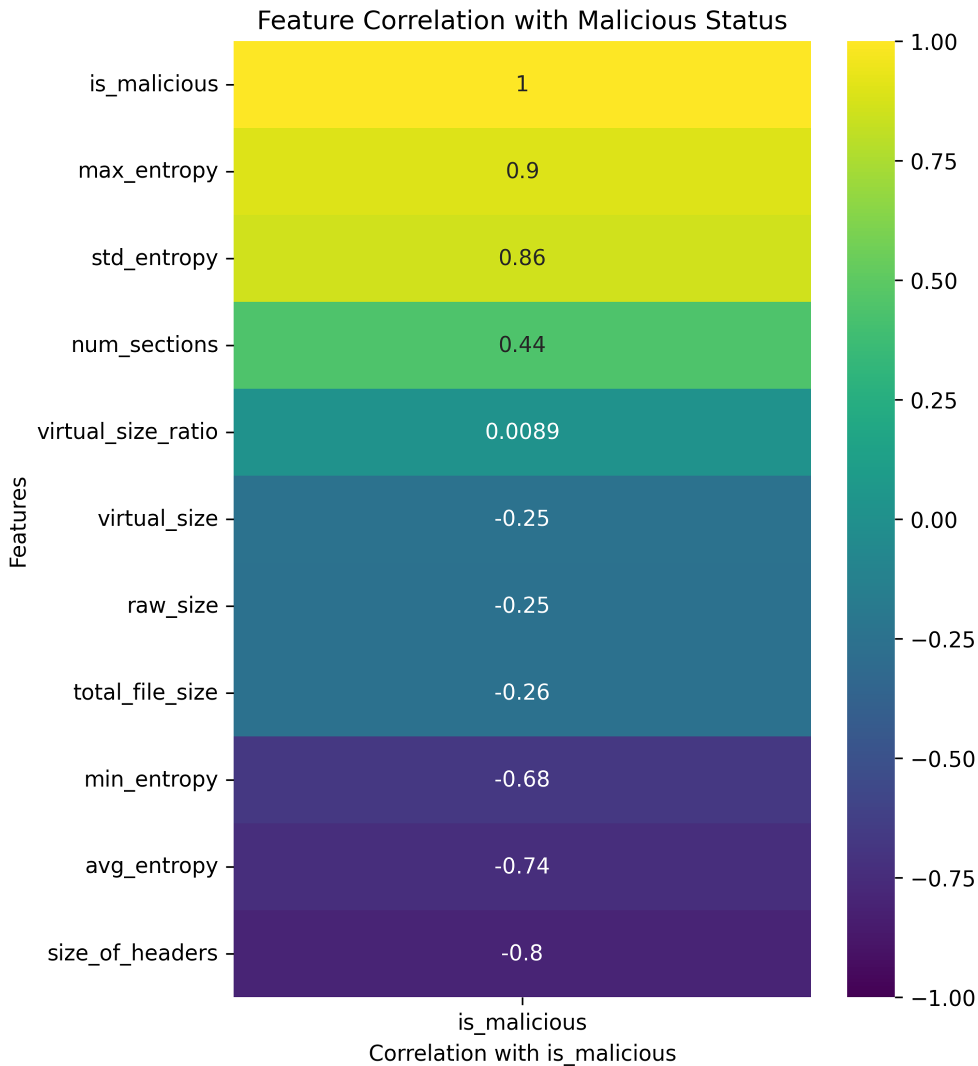
Why These Features Were Dropped

Dropped Feature	Reason
`filename`	Non-predictive (string identifier, not a signal)
`raw_size`	Multicollinear with `total_file_size`
`virtual_size`	Multicollinear with `raw_size` ; ratio captures the relationship

7.2 Exploratory Data Analysis (EDA)

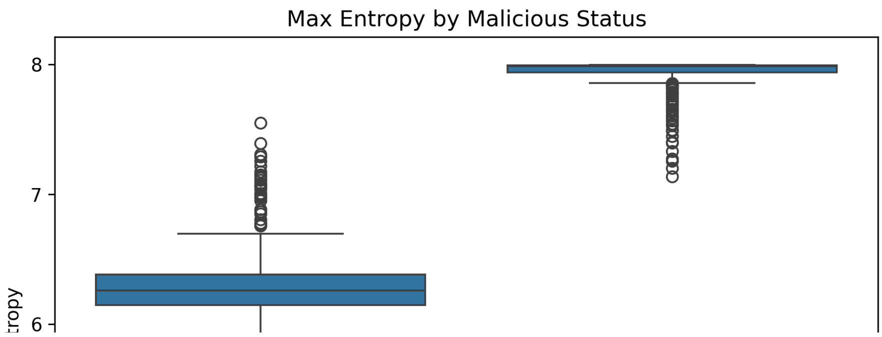
Before training, we visualized the dataset to understand feature relationships and validate our assumptions.

Feature Correlation with Target (`is_malicious`)



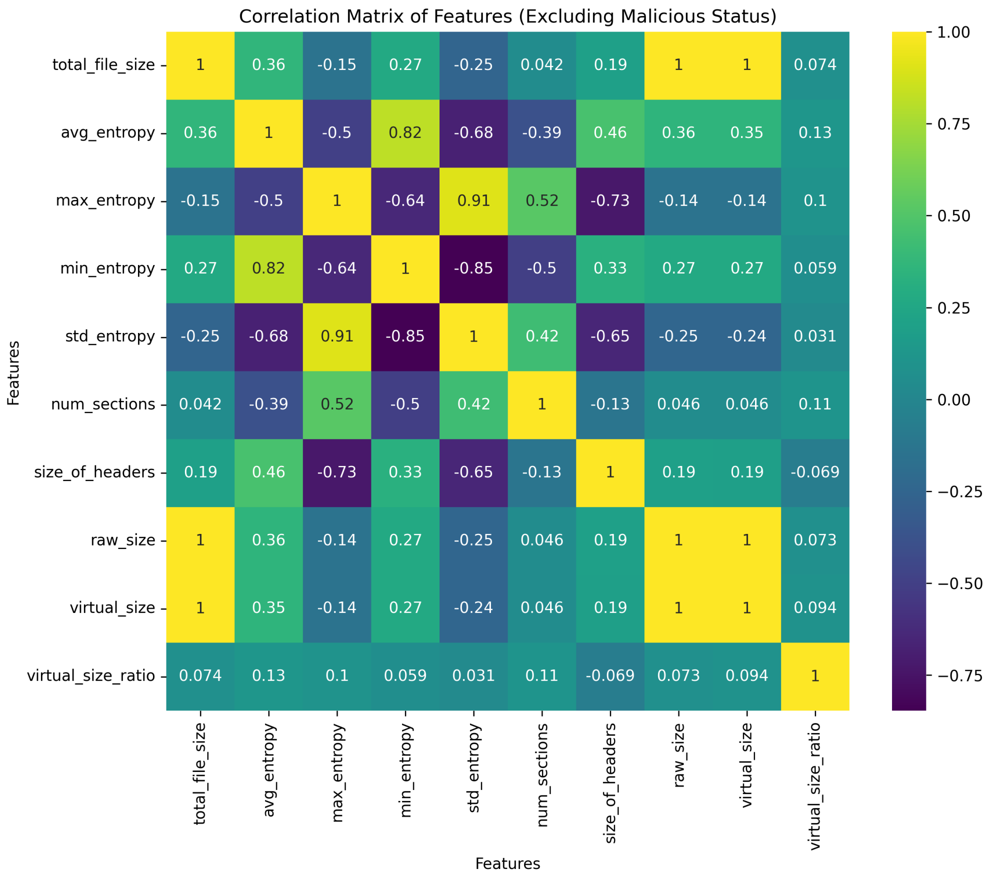
Insight: Shows which features have the strongest correlation with malware classification. Entropy features (`max_entropy` , `std_entropy`) show the highest positive correlation with `is_malicious` .

Max Entropy Distribution by Class



Insight: Clear separation between benign (class 0) and malicious (class 1) samples. Malware consistently shows higher `max_entropy` values (~7.5-8.0), while benign files cluster around 5.0-6.5. This visual confirms `max_entropy` is the strongest discriminator.

Multicollinearity Between Features



Insight: Reveals which features are redundant:

- `raw_size` and `virtual_size` are highly correlated (~0.95+) → dropped `raw_size`
- `virtual_size` and `total_file_size` overlap → kept `total_file_size`, dropped `virtual_size`
- `virtual_size_ratio` captures the relationship without redundancy

Why this matters: Multicollinear features don't add new information but can destabilize model coefficients and inflate feature importance scores.

7.3 Results: Perfect Classification 🎯

Confusion Matrix

```
               Predicted
               0      1
Actual  0   [ 99      0 ]
        1   [  0    100 ]
```

Metric	Value
True Negatives (Benign correct)	99
False Positives	0
False Negatives	0
True Positives (Malware correct)	100

Classification Report

Class	Precision	Recall	F1-Score	Support
0 (Benign)	1.00	1.00	1.00	99
1 (Malware)	1.00	1.00	1.00	100
Accuracy			**1.00**	**199**

7.4 Feature Importance Analysis (The "Why")

```
max_entropy          0.3275
std_entropy          0.2516
avg_entropy          0.1943
min_entropy          0.1149
size_of_headers      0.0612
total_file_size      0.0279
num_sections         0.0139
virtual_size_ratio   0.0086
```

Interpretation

Rank	Feature	Importance	What It Tells Us
1	`max_entropy`	32.75%	**The smoking gun** — encrypted payloads hit ~7.99 entropy
2	`std_entropy`	25.16%	Malware has *variance* (encrypted section vs. null padding)
3	`avg_entropy`	19.43%	Overall file complexity
4	`min_entropy`	11.49%	Benign files rarely have near-zero sections
5	`size_of_headers`	6.12%	Anomalous headers can indicate tampering
6-8	Others	< 3% each	Minor contributors

Key Insight: Entropy Features Dominate

The top 4 features are **all entropy-based**, accounting for **88.83%** of the model's decision-making power. This validates the project's core hypothesis:

> **Section-aware entropy analysis is the strongest signal for detecting packed/encrypted malware.**

7.5 Caveats & Next Steps

⚠️ **Why 100% accuracy might be misleading:**

Concern	Explanation
Synthetic data	Custom malware was generated with intentionally high entropy—real malware is more varied

Concern	Explanation
Small dataset	199 test samples; production needs 10,000+
No adversarial samples	Sophisticated malware uses entropy masking techniques

Recommended next steps:

1. Test on real-world malware samples (VirusTotal, MalwareBazaar)
2. Add adversarial samples (entropy-normalized malware)
3. Cross-validate with k-fold to ensure robustness

8. Future Improvements

- [ ] **Import Address Table (IAT) Analysis** — Detect suspicious API calls (`VirtualAlloc` , `WriteProcessMemory`)
- [ ] **Section Name Analysis** — Flag unusual names like `UPX0` , `.enigma`
- [ ] **String Extraction** — Find hardcoded C2 URLs or registry keys
- [ ] **YARA Rule Integration** — Cross-reference with known malware signatures
- [ ] **Batch Processing Pipeline** — Parallel extraction with `multiprocessing`
- [x] ~~**Train baseline model**~~ — Random Forest achieving 100% on synthetic dataset
- [ ] **Real-world validation** — Test on MalwareBazaar/VirusTotal samples

Appendix: Quick Reference

Shannon Entropy Formula

$$H(X) = -\sum_{i=0}^{255} p(x_i) \log_2 p(x_i)$$

Where $p(x_i)$ is the probability of byte value i appearing in the data.

Entropy Interpretation

Entropy Range	Meaning	Example

Entropy Range	Meaning	Example
0.0 - 1.0	Highly structured/repetitive	Null-padded sections
4.0 - 5.0	Plain text / code	`.text` section
7.0 - 8.0	Encrypted / compressed	AES payload, packed UPX

Document maintained as part of the EntropyX malware classification project.