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Study Finds Machine-Learning Models Identify North Macedonian Wine Varieties With Only 56% Accuracy

Researchers tested 1,024 wines across multiple vintages, with white-wine models reaching about 49% on unseen samples

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A study in the journal Beverages found that machine-learning models had only limited success when asked to identify North Macedonian wine varieties from routine physicochemical measurements, underscoring the gap between promising laboratory data and reliable real-world classification.

The research analyzed 1,024 wines from multiple vintages and tested whether standard analytical results could be used to distinguish among grape varieties. According to the study, the models performed modestly on unseen samples, reaching about 56% accuracy for red wines and about 49% for white wines. When the researchers reduced the number of input variables with principal component analysis, or PCA, performance

became weaker rather than better.

The findings point to a basic challenge in wine analytics: data that are easy to collect are not always enough to support strong classification. Routine physicochemical tests can capture broad characteristics of a wine, such as composition and general style, but the study suggests they may not provide a clear enough fingerprint to separate varieties consistently across different years of production.

That matters beyond academic research. In the beverage industry, companies and regulators are increasingly interested in using artificial intelligence to support authenticity checks, quality control and product verification. The new results suggest that expectations for such tools should remain measured when they rely mainly on standard laboratory variables. For wineries, importers and others in the trade, the study is a reminder that machine-learning systems may need stronger validation and possibly richer data before they are used for decisions involving labeling, traceability or fraud screening.

The multi-vintage design is also important. Vintage-to-vintage variation can change a wine’s measurable profile through weather, ripening patterns and production choices. A model that appears accurate within a narrow dataset can become less reliable when it faces wines made in different years. The study’s lower test results indicate that generalizing across vintages remains difficult, even when the wines come from the same country and the same broad category of analysis is applied.

The results also add nuance to the wider discussion around artificial intelligence in food and beverage analysis. Machine learning can detect patterns that are not obvious to human observers, but its output depends heavily on the type and quality of the input data. In this case, the signal available in routine physicochemical measurements appears to have been limited. The weaker results after PCA suggest that reducing the dataset to fewer combined variables removed information the models still needed.

The study does not mean machine learning has no role in wine classification. Instead, it indicates that routine physicochemical data alone may not be sufficient for accurate varietal identification in a demanding, real-world setting. More specialized analytical methods, larger datasets or models tailored to narrower classification tasks could still

improve results. But the evidence presented here suggests that claims of rapid AI-based authentication should be tested carefully before being translated into commercial or regulatory use.

For producers and buyers, that distinction is significant. A system that performs reasonably well in a training environment but only classifies about half of test samples correctly would be hard to rely on for high-stakes decisions. In wine, where origin, grape variety and authenticity can directly affect price and consumer trust, an error rate at that level could create practical and legal problems if used without additional checks.

The study therefore offers a more cautious view of AI in wine analysis. It shows that machine learning can find patterns in routine wine chemistry, but it also shows how quickly performance can fall when models are asked to classify new samples across multiple vintages. For the beverage sector, the message is less about abandoning AI than about setting realistic expectations and demanding strong external validation before these systems are treated as dependable tools.