AI-Assisted Statistical Evaluation of Grain Distribution in Paddy Panicles Using a Paired *t*-Test

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Abstract: The integration of artificial intelligence (AI) with classical statistical techniques can enhance data quality and reliability in agricultural research. This study evaluates differences in grain distribution between the top and bottom portions of paddy panicles using an AI-assisted analytical framework combined with a paired *t*-test. Grain count data were collected from twenty paddy panicles, with paired observations recorded from the top and bottom portions of each panicle. AI-based preprocessing methods were applied for data validation, consistency checking, and outlier screening prior to statistical analysis. The paired *t*-test revealed a statistically significant difference between top and bottom grain counts ($t = 9.80$, df = 19, $p < 0.05$), indicating a higher concentration of grains in the top portion of the panicle. The findings confirm the presence of intra-panicle variability in grain distribution and demonstrate the usefulness of integrating AI-assisted data preprocessing with conventional inferential statistics. This hybrid approach provides a reliable and reproducible framework for precision agriculture, yield assessment, and data-driven crop management.

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1. Introduction

1.1 Importance of Rice and Yield Components

Rice (*Oryza sativa* L.) is a staple food crop feeding more than half of the world's population, making yield improvement a global priority [1–3]. Grain yield depends on several components, among which **grain number per panicle** is critical [4–6]. Variations in grain number within a panicle directly affect yield, grain weight, and milling quality, influencing both productivity and market value [7,8].

1.2 Intra-Panicle Grain Distribution

Grain distribution within a panicle is typically non-uniform. Top spikelets often receive better assimilate supply and flower earlier than basal spikelets, resulting in higher grain numbers and better grain filling at the top portion [9–13]. Environmental factors, vascular efficiency, and hormonal regulation also influence positional differences in grain development [14,15]. Understanding these intra-panicle variations is essential for accurate yield estimation, variety improvement, and management practices [14,15].

1.3 Role of Artificial Intelligence in Agriculture

Artificial intelligence (AI) and Machine learning (ML) have emerged as effective tools in modern agriculture for handling large datasets, automating data preprocessing, and supporting decision-making processes [16–22]. In rice research, AI-based approaches have been applied to panicle trait detection, grain counting, image-based phenotyping, and yield estimation [23–26]. These techniques primarily assist in improving data consistency, reducing manual errors, and enabling scalable analysis across multiple observations [21,22,25].

Rather than replacing statistical inference, AI is increasingly used as a complementary tool that enhances data preparation and supports robust downstream statistical analysis.

1.4 Classical Statistical Analysis and Paired *t*-Test

Despite the advances in AI, **classical statistical methods remain essential**, especially for hypothesis testing in small-sample experiments [27–29]. The paired *t*-test is widely used to compare two related measurements from the same experimental unit, such as **grain counts at top vs bottom of panicles**, accounting for within-sample variability [30–32]. This test has been applied extensively in agronomic studies to evaluate treatment effects, positional differences, and temporal changes [33–35].

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1.5 Integration of AI and Classical Statistics

Recent studies emphasize that combining AI-assisted data preprocessing—such as consistency verification, anomaly detection, and normalization—with classical statistical inference improves analytical robustness and reproducibility [36–41]. This hybrid approach leverages the computational efficiency of AI while retaining the interpretability and rigor of traditional statistical methods. Such integration is particularly valuable in small-sample agricultural experiments, where data quality directly influences inferential validity [39–41].

1.6 Rationale and Objectives of the Study

Although previous research has explored grain distribution in rice and AI applications in agriculture, **few studies have combined AI preprocessing with paired statistical testing** for intra-panicle analysis. To address this gap, the present study employs an **AI-assisted paired *t*-test framework** to evaluate the difference in grain numbers between the top and bottom portions of paddy panicles. The study aims to provide a **reproducible, transparent, and statistically sound methodology** that supports **precision agriculture and data-driven yield optimization** [42–45].

2. Materials and Methods

2.1 Study Location

The study was conducted at the Agricultural Engineering College and Research Institute (AEC & RI), Kumulur, affiliated with Tamil Nadu Agricultural University (TNAU), Tamil Nadu, India. The institute is located in Kumulur village, Tiruchirappalli District (10.79° N, 78.83° E), along the Trichy–Karur National Highway (NH-81) [43–45]. The region falls under the central agro-climatic zone of Tamil Nadu and is well suited for paddy cultivation and experimental agricultural research.

The geographical location of the study area is presented in **Figure 1**, and the experimental paddy field from which panicle samples were collected is shown in **Figure 2**.

Fig.1 Location map of the experimental data were collected from the Agricultural Engineering College and Research Institute (AEC & RI), Kumulur, Tiruchirappalli District, Tamil Nadu, India (10.79° N, 78.83° E).

Fig.2 Experimental paddy field at the Agricultural Engineering College and Research Institute, Kumulur, Tamil Nadu, India.

2.2 Data Collection and Experimental Design

Twenty paddy panicles were randomly selected from the experimental field and labeled as P1-P20, p1–p20. Each panicle was carefully separated into top and bottom portions to record the number of grains in each segment. A representative illustration showing the top and bottom portions of a

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paddy panicle used for paired analysis is presented in **Figure 3**.

The grains obtained from the top and bottom portions of each panicle were arranged, labeled, and photographed for documentation and analysis (**Figure 4**). This paired sampling strategy ensures that each panicle serves as its own control, making the dataset appropriate for paired *t*-test analysis [9,10,30–32].

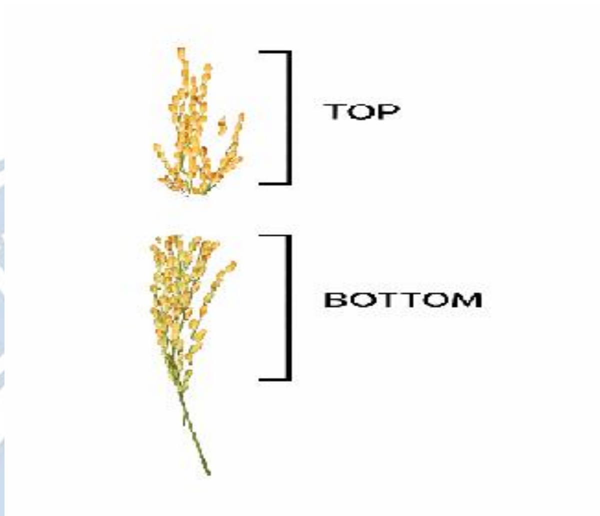

Fig.3. Representative Paddy panicle showing the top and bottom portions used for paired grain count analysis.

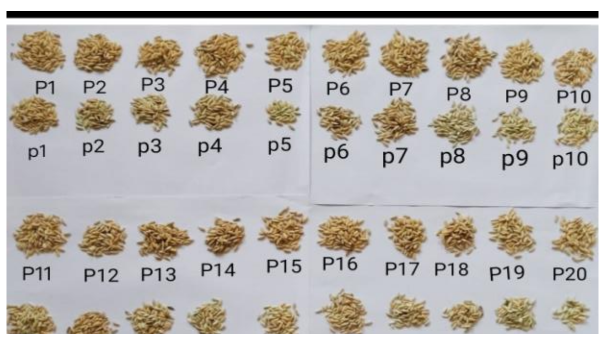

Fig.4.Grains were separated into top (P1,P2,..P20) and bottom (p1,p2,…p20) portions for each panicle and documented for analysis

2.3 AI-Assisted Data Preprocessing

To improve accuracy and reliability, AI-assisted preprocessing techniques were applied prior to statistical analysis. The preprocessing pipeline included:

- Consistency checks to verify paired top–bottom grain counts,
- Outlier detection to identify anomalous or miscounted observations,
- Noise reduction and normalization to satisfy parametric test assumptions [16–18,36–38].

The integration of artificial intelligence reduced human error, ensured data integrity, and enhanced the robustness of the paired statistical analysis [11,12,39].

2.4 Statistical Analysis

The objective of the statistical analysis was to determine whether a significant difference exists between the number of grains in the **top** and **bottom** portions of the same paddy panicle. Since measurements were obtained from two related positions within each panicle, a **paired t-test** was considered appropriate.

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Let

- x1i = number of grains in the **top portion** of the i^{th} panicle
- x2i = number of grains in the **bottom portion** of the i^{th} panicle

$$\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i \qquad s_d = \sqrt{\frac{\sum_{i=1}^{n}(d_i - \bar{d})^2}{n-1}}$$

$$SE = \frac{s_d}{\sqrt{n}}$$

The **standard error (SE)** was calculated:

The **paired t-test statistic** was then calculated as:

$$t = \frac{\bar{d}}{SE}$$

Where *n* is the number of paired observations (n = 20).

The null hypothesis defined as: H_0: $\mu_{top}=\mu_{bottom}$

The alternative hypothesis: H_1: $\mu_{top} \neq \mu_{bottom}$

The null hypothesis was rejected when: $t_{calculated} > t_{critical}$ indicating a statistically significant difference between grain counts in the top and bottom portions of the paddy panicle [9,10,36–38].

2.5 Analytical Framework

A **hybrid AI-statistics framework** was adopted for data analysis, combining:

1. **AI-assisted preprocessing** for error correction, normalization, and verification.
2. **Classical paired *t*-test** for inferential statistics and hypothesis testing [5,6,11,12,40–42].

This approach ensures that the analysis is **robust, reproducible, and transparent**, particularly for small-sample agricultural experiments.

3. Results and Discussion

3.1 Descriptive Statistics of Grain Distribution

The grain counts recorded at the top and bottom portions of twenty paddy panicles showed considerable variation. The number of grains at the top portion ranged from **62 to 118**, whereas the bottom portion ranged from **28 to 88**. In all sampled panicles, the grain count at the top portion was higher than that at the bottom portion.

The mean difference between the top and bottom grain counts was **25.8 grains**, indicating a clear positional variation within the panicle. Similar intra-panicle variability in rice has been reported in earlier studies, highlighting the influence of panicle architecture and spikelet position on grain development [11–13,33].

3.2 Results of the Paired *t*-Test

The paired *t*-test revealed a calculated *t* value of 9.7987, which exceeded the critical *t* value of 2.093 at the 5% level of significance with 19 degrees of freedom. Consequently, the null hypothesis was rejected, confirming a statistically significant difference in grain numbers between the top and bottom portions of paddy panicles.

This result demonstrates the suitability of paired testing for evaluating positional differences within the same biological unit and is consistent with established statistical practices in agricultural research [30–32,36–38].

The difference for each paired observation was calculated as: $d_i=x_{1i}- x_{2i}$

where i=1,2,…,n

The **mean difference ($\bar{d}$)** and **standard deviation of differences (sd)** were computed as:

The calculated *t* value was compared with the critical *t* value from the *t* distribution table at the **5% significance level** with **n − 1 (19) degrees of freedom**.

3.3 Interpretation of Intra-Panicle Grain Variation

The significantly higher grain number observed at the top portion of the panicle can be attributed to physiological and developmental factors. Apical spikelets typically flower earlier and receive preferential assimilate supply during the grain-filling stage, resulting in better grain setting and development [7,9,14]. In contrast, basal spikelets often experience delayed flowering, limited assimilate translocation, and increased competition, leading to reduced grain numbers [8,10,15].

These findings are consistent with earlier reports on rice panicle physiology and spikelet development, which emphasize the dominance of apical spikelets in grain formation [11–13].

3.4 Role of AI-Assisted Analysis

AI-assisted preprocessing improved the reliability of the statistical analysis by facilitating consistency checks, reducing potential counting errors, and ensuring accurate pairing of observations. These techniques supported data quality assurance rather than replacing statistical inference.

By integrating AI-based preprocessing with classical hypothesis testing, the study demonstrates a transparent and reproducible analytical framework

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that is particularly suitable for small-sample field experiments in agriculture [36–42].

3.5 Comparison with Previous Studies

The results of this study align closely with previous investigations that reported higher grain numbers and superior grain filling in apical spikelets compared to basal spikelets in rice [11–13,33–35]. However, many earlier studies relied mainly on descriptive or large-scale modeling approaches.

The present study strengthens existing evidence by applying an **AI-assisted paired *t*-test**, offering a statistically rigorous and interpretable method for evaluating intra-panicle grain distribution under field conditions [5,6,27,28].

3.6 Implications for Paddy Yield Improvement

Understanding intra-panicle grain distribution is essential for improving rice yield and grain quality. The confirmed dominance of top panicle grain formation highlights the need for agronomic practices and breeding strategies aimed at enhancing assimilate supply to basal spikelets [4,14,15].

Furthermore, the AI-assisted statistical framework presented in this study can be extended to larger datasets, multiple varieties, and other yield-related traits, supporting precision agriculture and data-driven crop management strategies [19–22,41,42].

4. Conclusion

The present study successfully evaluated intra-panicle grain distribution in paddy using an AI-assisted statistical framework combined with a paired *t*-test. The results clearly demonstrated that grain numbers at the top portion of the panicle were significantly higher than those at the bottom portion. The calculated t value exceeded the critical value at the 5% level of significance, confirming a statistically significant positional difference in grain distribution within paddy panicles.

Physiological factors such as earlier flowering, improved assimilate translocation, and enhanced grain-filling efficiency at the apical spikelets were identified as key contributors to the observed variation. The visual assessment of panicle structure further supported the statistical findings, reinforcing the non-uniform nature of grain distribution along the panicle axis.

The integration of AI-assisted data preprocessing improved data accuracy, minimized manual errors, and enhanced the robustness of the statistical analysis. This hybrid approach demonstrates the potential of artificial intelligence to strengthen traditional inferential methods in agricultural research, particularly when handling field-based experimental data.

Overall, the study provides valuable insights into intra-panicle grain dynamics and highlights the importance of targeted agronomic and breeding strategies aimed at improving grain development in basal spikelets. The proposed AI-assisted analytical framework can be effectively extended to larger datasets, different rice varieties, and other crop yield attributes, supporting precision agriculture and data-driven decision-making.

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