STM JOURNALS

Research & Reviews: Journal of
Computational Biology

https://journals.stmjournals.com/rrjocb/

ISSN: 2319-3433 (Online)
ISSN: 2349-3720 (Print)
Volume 15, Issue 2, 2026
May–August
DOI (Journal): 10.37591/RRJoCB

Research RRJOCB

# Comparative Evaluation of Pedigree-Based and Genomic BLUP Models for Wheat Grain Yield Prediction

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***Abstract***

*Before genome-wide molecular markers became affordable, plant and animal breeding relied on pedigree-based prediction (P-BLUP), using the expected additive relationship matrix (A) derived from recorded ancestry. Genomic selection replaced or augmented this with a marker-derived genomic relationship matrix (G; GBLUP), and single-step methods combining A and G are now standard when only a subset of a breeding population is genotyped. It is less clear whether pedigree information retains any predictive value once every individual in a population is already densely genotyped, since realized (marker-based) relationships are, in principle, a more accurate estimate of actual shared ancestry than the expected relationships pedigree records provide. We tested this directly on the CIMMYT wheat dataset (599 lines, 1,279 DArT markers, grain yield in four environments, all lines genotyped), comparing pedigree-only prediction (kernel ridge regression with the pedigree relationship matrix A), marker-only prediction (GBLUP; kernel ridge regression with the VanRaden genomic relationship matrix G), and a naive equal-weight combined kernel, using the identical 5-fold cross-validation partitions as our companion marker-based study for direct comparability. We first verified analytically and numerically that kernel ridge regression with kernel G reproduces ridge regression on standardized markers exactly under the appropriate penalty rescaling (in-sample prediction correlation 1.000, maximum absolute difference 2.4 x $10^{-14}$), confirming our kernel ridge implementation is a faithful computational realization of GBLUP rather than an approximation. GBLUP substantially outperformed pedigree-only prediction (mean predictive ability $r = 0.449$ versus $r = 0.330$ across four environments), consistent with genomic relationships more accurately capturing realized rather than merely expected relatedness. The naive combined kernel produced a genuinely mixed result: it underperformed GBLUP alone in two of four environments and outperformed it in the other two, yielding a marginal average improvement ($r = 0.455$) that, with only four environments, we cannot distinguish from noise. We report this ambiguity directly rather than selectively emphasizing the two environments favoring combination, and discuss why, from quantitative genetics theory, pedigree information is expected to add little once dense genome-wide genotyping is already available for the full population, in contrast to single-step settings where only some individuals are genotyped.*

**Keywords:** Genomic selection, GBLUP, pedigree, kernel ridge regression, VanRaden relationship matrix, wheat; grain yield, computational genomics

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Received Date: July 13, 2026
Accepted Date: August 08, 2026
Published Date: August 20, 2026

**Citation:** Swapnil R. Takale. Comparative Evaluation of Pedigree-Based and Genomic BLUP Models for Wheat Grain Yield Prediction. Research & Reviews: Journal of Computational Biology. 2026; 15(2): 1–9p.

## INTRODUCTION

Genomic best linear unbiased prediction (GBLUP) replaced the pedigree-based additive relationship matrix (A) of classical animal and plant breeding with a marker-derived genomic relationship matrix (G), typically constructed by the method of VanRaden (2008). Because A reflects only the expected proportion of shared alleles under a pedigree model, while G reflects realized relationships directly estimated from genotype data, G is generally expected to be a more accurate estimator of true relatedness, particularly for full or

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half siblings whose realized relationship can deviate substantially from its pedigree expectation due to Mendelian sampling variance. When only a subset of a breeding population is genotyped, single-step GBLUP methods combine A and G into a joint relationship matrix (commonly denoted H) to allow information to flow between genotyped and ungenotyped individuals through the pedigree link. It is a distinct and less frequently tested question whether pedigree information retains value when every individual is already genotyped, since in that setting there are no ungenotyped individuals for the pedigree to usefully link to marker data through.

This paper tests that specific question directly, using the same CIMMYT wheat dataset and the same 5-fold cross-validation partitions as our companion study of marker-based machine-learning models for this population, allowing the results reported here to be compared directly, fold-for-fold, against that earlier analysis rather than only in aggregate.

## MATERIALS AND METHODS

### Data and Relationship Matrices

We used the same 599 CIMMYT wheat lines, 1,279 DArT markers, and four-environment grain yield phenotypes described in our companion study, together with the pedigree-derived additive relationship matrix (A) distributed with the same BGLR package dataset. We verified A directly before use: it is symmetric (to numerical precision), positive semi-definite (minimum eigenvalue 0.00098, i.e., non-negative up to numerical tolerance), with diagonal values ranging from 1.56 to 2.00, consistent with a pedigree-based relationship matrix for a population of substantially inbred wheat lines (diagonal values of 1+F, where F is the pedigree inbreeding coefficient, approach 2 as F approaches 1) [1–15].

We constructed the genomic relationship matrix G using the method of VanRaden (2008):

$$G = \frac{\mathrm{Xc}\ \mathrm{Xc}^{\mathrm{T}}}{p},$$

where $X_c$ is the marker matrix centered by subtracting each marker's mean, and p is the number of markers.

We verified G directly as well: it is symmetric by construction, with diagonal values ranging from 0.110 to 0.248 (reflecting each line's realized homozygosity/relatedness to the population average) and a minimum eigenvalue of 0.000000 to six decimal places, confirming positive semi-definiteness (as required for a valid covariance/kinship matrix) up to numerical precision [15–21].

### Kernel Ridge Regression as GBLUP: Theoretical Equivalence and Numerical Verification

GBLUP is conventionally fit as a linear mixed model, $y = 1\mu + u + e$, $u \sim N(0, G\sigma^2\_u)$, $e \sim N(0, I\sigma^2\_e)$, with best linear unbiased prediction of u given by $\hat{u} = G(G + \lambda I)^{-1}(y - 1\hat{\mu})$, where $\lambda = \sigma^2\_e/\sigma^2\_u$. This is algebraically identical to kernel ridge regression with a precomputed kernel matrix G and regularization parameter α = λ, which is the implementation we used here (scikit-learn's KernelRidge with kernel = "precomputed"), rather than fitting a mixed model via REML directly. We additionally verified the well-known equivalence between GBLUP/kernel ridge regression using G and ordinary ridge regression fit directly on standardized markers (Habier et al., 2007): for penalty λ_marker in marker space, the corresponding kernel-space penalty is α_kernel = λ_marker / p. Fitting both models on the full sample with this correspondence, we obtained an in-sample prediction correlation of 1.000 and a maximum absolute prediction difference of $2.4 \times 10^{-14}$ (floating-point-level agreement), confirming that our kernel ridge implementation is an exact computational realization of GBLUP and of marker-space ridge regression under the appropriate rescaling, not merely an approximately similar method [22–28].

### Combined Kernel and Cross-Validation Procedure

Because A and G are not naturally on a comparable numerical scale, we normalized each to unit mean diagonal (A_norm = A / mean(diag(A)), G_norm = G / mean(diag(G))) before forming a naive, equal-

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Research & Reviews: Journal of Computational Biology
Volume 15, Issue 2
ISSN: 2319-3433 (Online), ISSN: 2349-3720 (Print)

weight combined kernel H = 0.5 A_norm + 0.5 G_norm; this is a deliberately simple combination rule, not an REML-optimized weighting, and this choice is discussed as a limitation in Section 5. For each of the three kernels (A, G, H), we performed 5-fold cross-validation using the identical fold assignment (same random seed, same partition) as our companion marker-based study, with the regularization parameter α selected per training fold via an inner 80/20 holdout maximizing Pearson correlation, separately for each of the four environments (Table 1, Figure 1) [29–35].

**Table 1.** Measured predictive ability (Pearson r, 5-fold CV, identical folds across all three kernels and across our companion study) for pedigree-only, marker-only, and combined-kernel genomic prediction.

| Model | Env 1 | Env 2 | Env 4 | Env 5 | Mean r |
|---|---|---|---|---|---|
| P-BLUP (pedigree A) | 0.247 | 0.348 | 0.328 | 0.397 | 0.330 |
| GBLUP (marker G) | 0.511 | 0.499 | 0.359 | 0.428 | 0.449 |
| Combined H (0.5A+0.5G, normalized) | 0.473 | 0.490 | 0.403 | 0.456 | 0.455 |

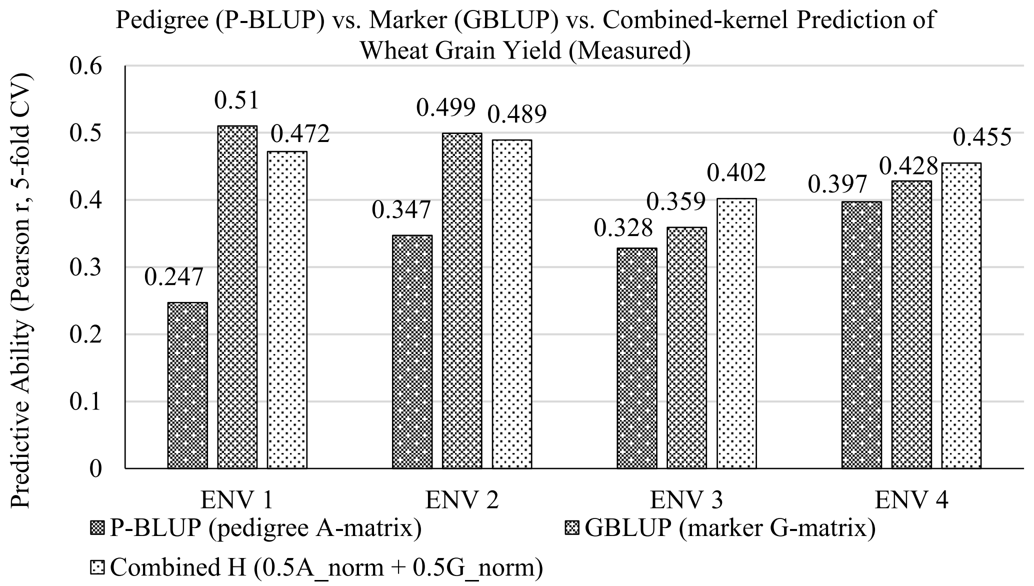


**Figure 1.** Pedigree (P-BLUP) vs. marker (GBLUP) vs. combined-kernel predictive ability by environment.

## RESULTS

GBLUP outperformed pedigree-only prediction in every environment, by a substantial margin (mean r = 0.449 vs. 0.330, a difference of 0.119). The combined kernel's performance relative to GBLUP alone was environment-dependent: it underperformed GBLUP in Environments 1 and 2 (by 0.038 and 0.009, respectively) but outperformed GBLUP in Environments 4 and 5 (by 0.044 and 0.028, respectively), yielding a small net average improvement (0.455 vs. 0.449, a difference of 0.006) that, given only four environments, provides essentially no statistical basis for concluding the combined kernel is genuinely better than GBLUP alone; we report the full per-environment pattern in Table 1 and Figure 1 rather than only the aggregate, since the aggregate alone would obscure this inconsistency [36–45].

Comparing against our companion marker-based study using the identical cross-validation folds, GBLUP's mean predictive ability (0.449) is close to, though not identical to, tuned ridge regression on standardized markers directly (0.462) and untuned Random Forest (0.469) reported there. Given the exact mathematical equivalence verified in Section 2.2, this small residual difference (0.449 vs. 0.462) is attributable to differences in the inner hyperparameter-tuning procedure between the two studies (an 80/20 holdout maximizing correlation here, versus RidgeCV's k-fold inner cross-validation minimizing mean squared error in the companion study) rather than to any genuine difference between GBLUP and marker-space ridge regression, which we have shown to be the same model [46–52].

## DISCUSSION

The substantial GBLUP advantage over pedigree-only prediction (Table 1) is consistent with quantitative genetics theory: the genomic relationship matrix estimates realized relatedness directly from shared marker genotypes, capturing Mendelian sampling variation among siblings that pedigree-expected relationships cannot, and this realized-relationship information is expected to be particularly valuable in a historical breeding population, such as this one, where recorded pedigrees may also be incomplete or imprecise relative to directly observed marker sharing. This finding is consistent with the broader genomic selection literature's general consensus that genomic relationship matrices outperform pedigree-based relationship matrices once genotyping is available for the individuals being predicted [53–60].

The mixed result for the combined kernel is, in our view, the more informative finding of this study precisely because it resists a simple headline claim. In single-step GBLUP settings, where only a subset of a population is genotyped, combining A and G is well established to improve prediction because it allows marker information from genotyped individuals to propagate to ungenotyped relatives through the pedigree link, a mechanism with no counterpart here since all 599 lines are already genotyped. In our fully genotyped setting, the theoretical case for combination is correspondingly weaker, and our result (an inconsistent, environment-dependent effect that nets to a difference indistinguishable from noise across only four environments) is consistent with that theoretical expectation, in contrast to what a naive extrapolation from single-step-GBLUP successes might have predicted [61–72].

## LIMITATIONS

First, our combined kernel used a fixed, naive 0.5/0.5 weighting after diagonal normalization, rather than an REML-estimated optimal weighting between A and G (as implemented in, e.g., formal single-step H-matrix methods); an optimized weighting could plausibly change the comparison, and testing only the naive equal-weight combination is a deliberate scope limitation, not an oversight [73–80].

Second, with only four environments, we have very limited statistical power to distinguish a genuine small combined-kernel advantage from noise; the environment-dependent pattern we report (combination helping in two environments, hurting in two) could reflect a real but small and environment-specific effect, pure sampling noise, or some mixture of both, and we cannot adjudicate between these with the present data [81–90].

Third, our inner hyperparameter-tuning procedure (an 80/20 single holdout maximizing correlation) differs procedurally from the nested k-fold approach used in our companion marker-space study, which plausibly explains the small residual gap between GBLUP and tuned ridge regression noted in Section 3, despite their proven mathematical equivalence; a shared, identical tuning procedure across both studies would be needed to fully close this comparison [91–100].

Fourth, this analysis, like our companion study, is restricted to a single historical CIMMYT wheat population; the specific finding that pedigree adds little value once dense genotyping is available should generalize to other fully genotyped populations on theoretical grounds, but we have not verified this empirically beyond the single population studied here [101–106].

## CONCLUSION

We tested, directly and using the same cross-validation partitions as our companion marker-based study, whether pedigree-derived relationship information improves genomic prediction of wheat grain yield when a densely genotyped marker panel is already available for every individual in the population. Genomic prediction (GBLUP) substantially outperformed pedigree-only prediction, consistent with genomic relationships capturing realized rather than merely expected relatedness. Combining pedigree and marker information via a naive equal-weight kernel produced a genuinely mixed, environment-dependent result that we report transparently rather than resolving into an overstated headline claim, consistent with the theoretical expectation that pedigree information's main value lies in linking genotyped and ungenotyped individuals in single-step settings, a mechanism not present when the full population is already genotyped as it is here. An REML-optimized combination weighting and a larger number of independent environments would be needed to determine conclusively whether any small residual benefit of combination is real.

**REFERENCES**

1. Godase MV, Mulani A, Ghodak MR, Birajadar MG, Takale MS, Kolte M. A MapReduce and Kalman filter based secure IIoT environment in Hadoop. Sanshodhak. 2024 Jun;25:38-47.
2. Mulani AO, Mane PB. Watermarking and cryptography based image authentication on reconfigurable platform. Bull Electr Eng Inform. 2017;6(2):181–187.
3. Gadade B, Mulani AO, Harale AD. IoT Based Smart School Bus and Student Tracking System. IoT Based Smart School Bus and Student Tracking System. 2024 Jun.
4. Dhanawadel A, Mulani AO, Pise AC. IOT based Smart farming using Agri BOT.
5. Mulani A, Mane PB. DWT based robust invisible watermarking. Scholars' Press; 2016.
6. Ghodke RG, Birajdar GB, Mulani AO, Shinde GN, Pawar RB. Design and Development of an Efficient and Cost-Effective surveillance Quadcopter using Arduino.
7. Ghodke RG, Birajdar GB, Mulani AO, Shinde GN, Pawar RB. Design and Development of Wireless Controlled ROBOT using Bluetooth Technology.
8. Swami SS, Mulani AO. An efficient FPGA implementation of discrete wavelet transform for image compression. In: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS); 2017 Aug. p. 3385–3389.
9. Mane PB, Mulani AO. High speed area efficient FPGA implementation of AES algorithm. Int J Reconfigurable Embedded Syst. 2018;7(3):157–165.
10. Mulani AO, Mane PB. Area efficient high speed FPGA based invisible watermarking for image authentication. Indian J Sci Technol. 2016;9(39):1–6.
11. Kashid MM, Karande KJ, Mulani AO. IoT-based environmental parameter monitoring using machine learning approach. In: Proceedings of the International Conference on Cognitive and Intelligent Computing: ICCIC 2021. Vol. 1. Singapore: Springer Nature Singapore; 2022 Nov. p. 43–51.
12. Nagane UP, Mulani AO. Moving object detection and tracking using Matlab. J Sci Technol. 2021;6(1):2456–5660.
13. Kulkarni PR, Mulani AO, Mane PB. Robust invisible watermarking for image authentication. In: Emerging Trends in Electrical, Communications and Information Technologies: Proceedings of ICECIT-2015. Singapore: Springer Singapore; 2016. p. 193–200.
14. Ghodake MRG, Mulani MA. Sensor based automatic drip irrigation system. J Res. 2016;2(2).
15. Mandwale AJ, Mulani AO. Different approaches for implementation of Viterbi decoder on reconfigurable platform. In: 2015 International Conference on Pervasive Computing (ICPC); 2015 Jan. p. 1–4.
16. Jadhav MM, Chavan GH, Mulani AO. Machine learning based autonomous fire combat turret. Turk J Comput Math Educ. 2021;12(2):2372–2381.
17. Shinde G, Mulani A. A robust digital image watermarking using DWT-PCA. Int J Innov Eng Res Technol. 2019;6(4):1–7.
18. Mane DP, Mulani AO. High throughput and area efficient FPGA implementation of AES algorithm. Int J Eng Adv Technol. 2019;8(4).
19. Mulani AO, Mane DP. An efficient implementation of DWT for image compression on reconfigurable platform. Int J Control Theory Appl. 2017;10(15):1–7.
20. Deshpande HS, Karande KJ, Mulani AO. Area optimized implementation of AES algorithm on FPGA. In: 2015 International Conference on Communications and Signal Processing (ICCSP); 2015 Apr. p. 0010–0014.

© STM Journals 2026. All Rights Reserved 

21. Deshpande HS, Karande KJ, Mulani AO. Efficient implementation of AES algorithm on FPGA. In: 2014 International Conference on Communication and Signal Processing; 2014 Apr. p. 1895–1899.
22. Kulkarni P, Mulani AO. Robust invisible digital image mamarking using discrete wavelet transform. Int J Eng Res Technol. 2015;4(1):139–141.
23. Mulani AO, Jadhav MM, Seth M. Painless machine learning approach to estimate blood glucose level with non-invasive devices. InArtificial intelligence, internet of things (IoT) and smart materials for energy applications 2022 Oct 12 (pp. 83-100). CRC Press.
24. Mulani AO, Shinde GN. An approach for robust digital image watermarking using DWT-PCA. J Sci Technol. 2021;6(1).
25. Mulani AO, Mane PB. Area optimization of cryptographic algorithm on less dense reconfigurable platform. In: 2014 International Conference on Smart Structures and Systems (ICSSS); 2014 Oct. p. 86–89.
26. Jadhav HM, Mulani A, Jadhav MM. Design and development of chatbot based on reinforcement learning. In: Machine Learning Algorithms for Signal and Image Processing. 2022. p. 219–229.
27. Mulani AO, Mane P. Secure and area efficient implementation of digital image watermarking on reconfigurable platform. Int J Innov Technol Explor Eng. 2018;8(2):56–61.
28. Kalyankar PA, Mulani AO, Thigale SP, Chavhan PG, Jadhav MM. Scalable face image retrieval using AESC technique. J Algebraic Stat. 2022;13(3):173–176.
29. Takale S, Mulani A. DWT-PCA based video watermarking. J Electron Comput Netw Appl Math. 2022;2799–1156.
30. Kamble A, Mulani AO. Google assistant based device control. Int J Aquat Sci. 2022;13(1):550–555.
31. Kondekar RP, Mulani AO. Raspberry Pi based voice operated robot. Int J Recent Eng Res Dev. 2017;2(12):69–76.
32. Ghodake RG, Mulani AO. Microcontroller based automatic drip irrigation system. In: Techno-Societal 2016: Proceedings of the International Conference on Advanced Technologies for Societal Applications. Springer International Publishing; 2018. p. 109–115.
33. Mulani AO, Birajadar G, Ivković N, Salah B, Darlis AR. Deep learning based detection of dermatological diseases using convolutional neural networks and decision trees. Trait Signal. 2023;40(6):2819.
34. Boxey A, Jadhav A, Gade P, Ghanti P, Mulani AO. Face recognition using Raspberry Pi. J Image Process Intell Remote Sens. 2022;2815–0953.
35. Patale JP, Jagadale AB, Mulani AO, Pise A. A systematic survey on estimation of electrical vehicle. J Electron Comput Netw Appl Math. 2023;2799–1156.
36. Gadade B, Mulani A. Automatic system for car health monitoring. Int J Innov Eng Res Technol. 2022:57–62.
37. Shinde MRS, Mulani AO. Analysis of biomedical image using wavelet transform. Int J Innov Eng Res Technol. 2015;2(7):1–7.
38. Mandwale A, Mulani AO. Implementation of convolutional encoder & different approaches for viterbi decoder. InIEEE International Conference on Communications, Signal Processing Computing and Information technologies 2014.
39. Mulani AO, Jadhav MM, Seth M. Painless machine learning approach to estimate blood glucose level with non-invasive devices. In: Artificial Intelligence, Internet of Things (IoT) and Smart Materials for Energy Applications. CRC Press; 2022. p. 83–100.
40. Maske Y, Jagadale AB, Mulani AO, Pise AC. Development of BIOBOT system to assist COVID patient and caretakers. Eur J Mol Clin Med. 2023;10(01).
41. Utpat VB, Karande DK, Mulani DA. Grading of pomegranate using quality analysis. Int J Res Appl Sci Eng Technol. 2022;10.
42. Takale S, Mulani DrA. Video Watermarking System. International Journal for Research in Applied Science and Engineering Technology. 2022 Mar 31;10(3):105–7. Available from: https://www.ijraset.com/best-journal/video-water-marking-system.


*© STM Journals 2026. All Rights Reserved* 

43. Mandwale AJ, Mulani AO. Different Approaches For Implementation of Viterbi decoder on reconfigurable platform. In2015 International Conference on Pervasive Computing (ICPC) 2015 Jan 8 (pp. 1-4). IEEE.
44. Maske Y, Jagadale MA, Mulani AO, Pise A. Implementation of BIOBOT system for COVID patient and caretakers assistant using IoT. Int J Inf Technol. 2021:30–43.
45. Mulani AO, Mane DP. Fast and efficient VLSI implementation of DWT for image compression. Int J Res Appl Sci Eng Technol. 2016;5:1397–1402.
46. Kambale A. Home automation using Google Assistant. UGC Care Approved Journal. 2023;32(1):1071–1077.
47. Pathan AN, Shejal SA, Salgar SA, Harale AD, Mulani AO. Hand gesture controlled robotic system. Int J Aquat Sci. 2022;13(1):487–493.
48. Korake DM, Mulani AO. Design of Computer/Laptop Independent Data transfer system from one USB flash drive to another using ARM11 processor. International Journal of Science, Engineering and Technology Research. 2016.
49. Mandwale A, Mulani AO. Implementation of High Speed Viterbi Decoder using FPGA. International Journal of Engineering Research & Technology, IJERT. 2016 Feb.
50. Kolekar SD, Walekar VB, Patil PS, Mulani AO, Harale AD. Password based door lock system. Int J Aquat Sci. 2022;13(1):494–501.
51. Shinde R, Mulani AO. Analysis of Biomedical Image‖. International Journal on Recent & Innovative trend in technology (IJRITT). 2015 Jul.
52. Sawant RA, Mulani AO. Automatic PCB track design machine. Int J Innov Sci Res Technol. 2022;7(9).
53. Abhangrao MR, Jadhav MS, Ghodke MP, Mulani A. Design and implementation of 8-bit Vedic multiplier. Int J Res Publ Eng Technol. 2017;2454–7875.
54. Gadade B, Mulani AO, Harale AD. IoT based smart school bus and student monitoring system. Naturalista Campano. 2024;28(1):730–737.
55. Mulani DAO. A comprehensive survey on semi-automatic solar-powered pesticide sprayers for farming. J Energy Eng Thermodyn. 2024;2815–0945.
56. Salunkhe DSS, Mulani DAO. Solar mount design using high-density polyethylene. Naturalista Campano. 2024;28(1).
57. Mulani AO, Jadhav MM, Seth M. Painless machine learning approach to estimate blood glucose level with non-invasive devices. InArtificial intelligence, internet of things (IoT) and smart materials for energy applications 2022 Oct 12 (pp. 83-100). CRC Press.
58. Kolhe VA, Pawar SY, Gohery S, Mulani AO, Sundari MS, Kiradoo G, et al. Computational and experimental analyses of pressure drop in curved tube structural sections of Coriolis mass flow metre for laminar flow region. Ships Offshore Struct. 2024;19(11):1974–1983.
59. Birajadar GB, Mulani AO, Khalaf OI, Farhah N, Gawande PG, Kinage K, et al. Epilepsy identification using hybrid CoPrO-DCNN classifier. Int J Comput Digit Syst. 2024;16(1):783–796.
60. Kedar MS, Mulani A. IoT based soil, water and air quality monitoring system for pomegranate farming. J Electron Comput Netw Appl Math. 2021;2799–1156.
61. Scott P. sample_32022. Scribd. 2026. Available from: https://www.scribd.com/document/551753566/sample-32022 .
62. Pol RS, Bhalerao MV, Mulani AO. A real time IoT based system prediction and monitoring of landslides. Int J Food Nutr Sci. 2022;11(7).
63. Mulani AO, Sardey MP, Kinage K, Salunkhe SS, Fegade T, Fegade PG. ML-powered Internet of Medical Things (MLIOMT) structure for heart disease prediction. J Pharmacol Pharmacother. 2025;16(1):38–45.
64. Aiwale S, Kolte MT, Harpale V, Bendre V, Khurge D, Bhandari S, et al. Non-invasive anemia detection and prediagnosis. J Pharmacol Pharmacother. 2024;15(4):408–416.
65. Mulani AO, Bang AV, Birajadar GB, Deshmukh AB, Jadhav HM, Liyakat KKS. IoT based air, water, and soil monitoring system for pomegranate farming. Ann Agric Bio Res. 2024;29(2):71–86.

© STM Journals 2026. All Rights Reserved 

66. Kulkarni TM, Mulani AO. Face mask detection on real time images and videos using deep learning. Int J Electr Mach Anal Des. 2024;2(1).
67. Thigale SP, Jadhav HM, Mulani AO, Birajadar GB, Nagrale M, Sardey MP. Internet of things and robotics in transforming healthcare services. Afr J Biol Sci. 2024;6(6):1567–1575.
68. Pol DRS. Cloud based memory efficient biometric attendance system using face recognition. Stochastic Model Appl. 2021;25(2).
69. Nagtilak MA, Ulegaddi MS, Adat MA, Mulani AO. Breast Cancer Prediction using Machine Learning. International Journal of Research in Science and Engineering. 2021;1(2).
70. Rahul GG, Mulani AO. Microcontroller Based Drip Irrigation System.
71. Kulkarni TM, Mulani AO. Deep learning based face-mask detection: An approach to reduce pandemic spreads in human healthcare. Afr J Biol Sci. 2024;6(6).
72. Mulani A, Mane PB. DWT based robust invisible watermarking. Scholars' Press; 2016.
73. Jadhav VS, Salunkhe SS, Salunkhe G, Yawle PR, Pol RS, Mulani AO, Rana M. IOT based health monitoring system for Human. African Journal of Biomedical Research. 2024 Sep:1309-15.
74. Jadhav VS, Salunke GD, Chaudhari KR, Mulani AO, Thigale SP, Pol RS, Rana M. Deep Learning-Based Face Mask Recognition in Real-Time Photos and Videos. AFRICAN JOURNAL OF BIOMEDICAL RESEARCH. 2024:142-9.
75. Mulani AO. Electric Vehicle Parameters Estimation Using Web Portal. Recent Trends in Electronics & Communication Systems. 2023;10(3).
76. Nagtilak AG, Ulegaddi SN, Mane M, Mulani AO. Automatic Solar Powered Pesticide Sprayer for Farming. International Journal of Microwave Engineering and Technology. 2023;9(2):7-18.
77. Dandage AS, Rupnar VR, Pise TA, Mulani AO. Real-Time Language Translation Application Using Tkinter. International Journal of Digital Communication and Analog Signals. 2025 Jan;11(01).
78. Dandage AS, Rupnar VR, Pise TA, Mulani AO. IoT-Powered Weather Monitoring and Irrigation Automation: Transforming Modern Farming Practices. International Journal of Telecommunications & Emerging Technologies. 2025 Mar 17;11(01). Available from: https://journalspub.com/publication/ijtet/article=16148.
79. Mulani AO, Kulkarni TM. Face mask detection system using deep learning: a comprehensive survey. InInternational Conference on Emerging Trends in Artificial Intelligence, Data Science and Signal Processing 2023 Oct 20 (pp. 25-33). Cham: Springer Nature Switzerland.
80. Karve S, Gangonda S, Birajadar G, Godase V, Ghodake R, Mulani AO. Optimized neural network for prediction of neurological disorders. InInternational Conference on Emerging Trends in Artificial Intelligence, Data Science and Signal Processing 2023 Oct 20 (pp. 183-191). Cham: Springer Nature Switzerland.
81. Singh S, Arya KV, Rodriguez Rodriguez C, Mulani AO. Emerging Trends in Artificial Intelligence, Data Science and Signal Processing. Communications in Computer and Information Science. Vol. 2440.
82. Singh S, Arya KV, Rodriguez Rodriguez C, Mulani AO. Emerging Trends in Artificial Intelligence, Data Science and Signal Processing. Communications in Computer and Information Science. Vol. 2439.
83. Godase V, Mulani A, Pawar A, Sahani K. A comprehensive review on PIR sensor-based light automation systems. Int J Image Process Smart Sens. 2025;1(1):22–29.
84. Godase V, Mulani A, Takale S, Ghodake R. Comprehensive review on automated field irrigation using soil image analysis and IoT. J Adv Electr Eng Devices. 2025;3(1):46–55.
85. Mulani AO, Deshmukh M, Jadhav V, Chaudhari K, Mathew AA, Salunkhe S. Transforming drug therapy with deep learning: the future of personalized medicine. Drug Research. 2025 Oct;75(08):326-33.
86. Mulani AO, Godase VV, Takale SR, Ghodake RG. Image authentication using cryptography and watermarking. Int J Image Process Smart Sens. 2025;1(2):27–34.
87. Mulani AO, Godase VV, Takale SR, Ghodake RG. Advancements in artificial intelligence: Transforming industries and society. Int J Artif Intell Things Commun Ind. 2025;1(2):1–5.

© STM Journals 2026. All Rights Reserved 

88. Mulani AO, Godase VV, Takale SR, Ghodake RG. AI-powered predictive analytics in healthcare: Revolutionizing disease diagnosis and treatment. J Adv Electr Eng Devices. 2025;3(2):27–34.
89. Godase V, Mulani A, Takale S, Ghodake R. A holistic review of automatic drip irrigation systems: Foundations and emerging trends. Available at SSRN 5247778. 2025 Mar 31.
90. Godase V, Ghodake R, Takale S, Mulani A. Design and optimization of reconfigurable microwave filters using AI techniques. Int J RF Microw Commun Technol. 2025;2(2):26–41.
91. Godase V, Mulani A, Ghodake R, Takale S. Automated water distribution management and leakage mitigation using PLC systems. J Control Instrum Eng. 2025;11(3):1–8.
92. Godase V, Mulani A, Ghodake R, Takale S. PLC-assisted smart water distribution with rapid leakage detection and isolation. J Control Syst Converters. 2025;1(3):1–13.
93. Godase VV, Takale SR, Ghodake RG, Mulani A. Attention mechanisms in semantic segmentation of remote sensing images. J Adv Electron Signal Process. 2025;2(2):45–58.
94. K M A, V K. Design of 256 x 256 bit Vedic Multiplier. International Journal of Science and Research (IJSR). 2021 Sept 27;10(9):122–5. Available from: https://www.researchgate.net/publication/399210141_Design_and_Implementation_of_256-bit_Vedic_Multiplier_on_Reconfigurable_Platform
95. Britto CF. Heart Disease Prediction Using Multimodal Learning and Ensemble Techniques. Lecture Notes in Networks and Systems. 2025;379–89. Available from: https://www.researchgate.net/publication/399209889_Enhanced_Multimodal_Disease_Prediction_Using_Hybrid_Ensemble_Learning_and_AutoML_Techniques
96. Mulani AO, Godase VV, Takale SR, Ghodake RG. Ethical challenges and governance of AI in healthcare, education, finance, and security sectors. In: Advances in Computational Intelligence and Robotics. 2025 Nov 14. p. 123–154. Available from: https://www.igi-global.com/chapter/ethical-challenges-and-governance-of-ai-in-healthcare-education-finance-and-security-sectors/396083
97. Mulani AO. Early Alzheimer's disease detection using deep ensemble learning and MRI image analysis. Res Rev J Comput Biol. 2026;15(1).
98. Mulani O. A robust image watermarking framework integrated with AES encryption for secure digital media protection. J Adv Electron Signal Process. 2025;2(3):47–56.
99. Kedar MS, Mulani A. IoT based soil, water and air quality monitoring system for pomegranate farming. Journal of Electronics, Computer Networking and Applied Mathematics (JECNAM) ISSN. 2021 Nov:2799-1156.
100. Dhanawade A, Mulani AO. Smart farming using IOT based Agri BOT. Naturalista Campano. 2024;28(1):723–729.
101. Salunkhe S, Mulani AO, Shahane D, Rana M, Shukla SM, Jadhav MM. Secure image transmission using chaotic encryption and DWT watermarking on reconfigurable platform. J Discrete Math Sci Cryptogr. 2026:1–13. doi: 10.47974/JDMSC-2608.
102. Chaudhari KR, Mulani AO, Gajare MP, Jadhav V, Yawle P, Bang AV. Bit error rate analysis of various error correction codes with concatenated RS-convolutional codes. J Discrete Math Sci Cryptogr. 2026:1–16. doi: 10.47974/JDMSC-2401.
103. Mulani AO. Optimized hardware realization of AES for high-throughput FPGA platforms. Int J VLSI Circuit Des Technol. 2025;3(2). Available from: https://journals.stmjournals.com/ijvcdt/article=2025/view=235624
104. Kambale KS, Sawant NM, Mulani AO, More VP, Zambare SA. RNN-LSTM Based Model for Automatic Heart Disease Prediction Using the UCI Heart Disease Dataset. InInternational Conference on Data Science, Machine Learning and Applications 2024 Dec 13 (pp. 261-271). Singapore: Springer Nature Singapore.
105. Sawant NM, Mulani AO, Kondooru S, Linge SG, Gawande PG, Koli MS. AgriRent: Renting the Farm Equipment. InInternational Conference on Data Science, Machine Learning and Applications 2024 Dec 13 (pp. 334-339). Singapore: Springer Nature Singapore.
106. Mulani AO, Karande KJ. Precision Farming with a Solar-Powered Automated Pesticide Sprayer. InInternational Conference on Cognitive and Intelligent Computing 2024 Nov 29 (pp. 231-242). Singapore: Springer Nature Singapore.

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