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Can artificial intelligence be trained to account for the growth laws and biological patterns inherent in tree growth?

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Abstract: This study addresses a fundamental question in artificial intelligence applications within forestry science: Can AI models effectively learn and incorporate inherent biological growth patterns and laws governing tree development? Through systematic evaluation of Deep Learning Architecture (DLA) implementations in forestry modeling, we identify two distinct methodological paradigms: conventional adaptive learning-based models and optimized DLA frameworks incorporating hyperparameter and regularization techniques. While AI models demonstrate superior statistical performance compared to traditional regression approaches, their evaluation in forestry science necessitates consideration beyond mere performance metrics, particularly regarding biological plausibility. Our analysis reveals that standard adaptive learning-based AI models, despite achieving high training accuracy, often exhibit overfitting tendencies and fail to capture fundamental biological relationships. In contrast, hyperparameter-optimized and regularization-optimized DLA models, incorporating customized network parameters, demonstrate remarkable capacity in maintaining biological fidelity while mitigating overfitting challenges. These optimized frameworks successfully predict tree attributes while preserving consistency with established dendrometric principles, effectively addressing the traditional 'black-box' limitations of AI models. The study concludes that through proper optimization techniques, AI models can indeed be trained to account for biological growth patterns, though their full potential in forestry applications remains to be explored as our understanding of their capabilities continues to evolve.

Keywords: biological realistic predictions, overfitting, hyperparameter-optimized and regularization-optimized DLA models

1. Introduction

In the mid-nineteenth century, Alan Turing's influential 1950 paper in the Journal of Mind introduced a pivotal question by juxtaposing two concepts: 'thinking' and 'machines' through his inquiry, 'Can machines think?' (Turing, 1950). This foundational concept of thinking machines has evolved into Artificial Intelligence (AI) systems capable of learning the dynamic mechanisms and interrelationships within living ecosystems (McCorduck, 2004; Nilsson, 2014). Turing's initial question has transformed into a more complex inquiry: 'Can artificial intelligence (AI) learn and comprehend living systems, such as forest ecosystems?'

From this perspective, a critical initial phase in developing AI systems involves enabling AI to gain comprehensive understanding of the living systems it encounters (Russell et al., 2015; Brynjolfsson and Mitchell, 2017). The predictive capabilities and effective learning processes of AI in relation to these living systems represent crucial developmental stages in AI model evolution (Armstrong et al., 2014; Taddeo and Floridi, 2018). Consequently, AI techniques increasingly focus on the quality of learning required to accurately model these complex biological systems.

Artificial Intelligence (AI) models have demonstrated remarkable success in learning processes across various engineering disciplines, including electronics, manufacturing, mechanical engineering, communications, and construction. Moreover, these models exhibit significant potential for understanding the complex interrelationships within natural ecosystem growth processes, particularly in forest systems.

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Since the early 2000s, AI models—specifically Artificial Neural Network (ANN) models—have emerged as an innovative and increasingly prominent prediction methodology in forest modeling studies. The growing prominence of ANN models in forestry modeling literature can be attributed to two key advantages: first, their robust capability for nonlinear modeling without the need for predetermined statistical functions, and second, their ability to generate successful and robust predictions without adhering to traditional statistical assumptions (Özçelik et al., 2010; Ashraf et al., 2013; Diamantopoulou et al., 2015). Many studies focused on developing and evaluating ANN models by comparing their predictive capabilities for various individual tree and stand characteristics against conventional regression models—the latter having served as the classical statistical estimation methodology in forestry for approximately eight decades. Comparative analyses consistently demonstrated that ANN models exhibited superior predictive performance in estimating individual tree and stand attributes compared to traditional regression approaches. In this evolving landscape of predictive modeling, AI models—particularly ANN models and more recently, Deep Learning Architecture (DLA) models—have emerged as viable alternatives to classical regression approaches. This shift is particularly significant given the longstanding criticisms of AI models with ANN or DLA regarding their reliance on biological assumptions and limitations in modeling complex growth relationships within tree and forest systems, especially in certain data structures. In forestry biometrics, while statistical validity and model fit are essential criteria, the biological realism of predicted individual tree and stand attributes holds paramount importance. This emphasis on biological realism was first articulated by Levins (1966), who established it as a fundamental requirement for developing robust and predictive models in forest systems. Subsequently, Lei and Parresol (2001) further advanced this concept by delineating specific biologically realistic characteristics crucial for modeling individual tree growth.

Within this theoretical framework, prediction systems developed for forestry applications must demonstrate consistency with established biological growth patterns. These patterns typically manifest as sigmoid growth curves with distinct inflection points, multiple asymptotes, and monotonically non-decreasing trajectories over time—characteristics that reflect the underlying biological processes of tree and forest development. This study evaluates the potential of artificial intelligence models, particularly Deep Learning Architecture (DLA) models, to generate predictions that align with biological realism and fundamental growth laws governing both individual tree and stand development in forestry. The present research may explore the fundamental challenge of training artificial intelligence systems to effectively recognize and account for the inherent biological patterns and growth laws that characterize tree development processes within forest ecosystems.

2. Overfitting problem: A significant challenge and limitation in artificial intelligence

AI models, characterized by multiple non-linear hidden layers and thousands of neuronal weights, demonstrate remarkable flexibility and non-linear modeling capabilities in their complex architectural structures when modeling various individual tree and stand attributes. While this inherent flexibility in non-linear modeling potentially offers superior predictive performance compared to traditional linear and non-linear regression approaches, it simultaneously introduces the risk of overfitting during the training process. In overfitted challenges, AI models may generate predictions that almost perfectly align with observed training data, effectively memorizing the dataset—including its noise components—rather than learning the fundamental input-output relationships. This phenomenon, formally known as the 'overfitting or generalization problem,' represents a critical limitation that frequently impairs the model's ability to generalize effectively to unseen or validation datasets.

The manifestation of overfitting typically presents as a distinct pattern: while the model achieves exceptionally low residual errors for the training dataset, it exhibits substantially larger errors when applied to unseen validation data. Consequently, overfitted AI models often demonstrate poor statistical performance metrics when evaluated against validation datasets. The hallmark symptoms of overfitting and generalization problems can be characterized by low bias in training set predictions coupled with high variance and unsatisfactory predictive capability when applied to validation datasets.

The implications of the overfitting problem extend beyond mere validation error metrics, significantly impacting the ability to achieve biological realism in modeling individual tree and stand growth dynamics within forestry science. When AI models succumb to overfitting, failing to learn intrinsic data relationships and instead defaulting to memorization patterns, they may fundamentally violate principles of biological realism. The core

challenge with overfitted AI models lies in their tendency to memorize rather than learn the underlying relationships in the training data, thereby compromising their ability to capture genuine biological patterns and growth dynamics.

3. The hyperparameter-optimized or regularization-optimized AI models

In addressing the overfitting phenomenon within artificial intelligence frameworks, the optimization of hyperparameters and regularization parameters emerges as a critical component in the development of AI models. Neural network architectures incorporating such optimized hyperparameters are formally classified as 'hyperparameter-optimized ANN' models, reflecting their enhanced configurational sophistication. Also, Within the artificial intelligence literature, AI models incorporating optimized regularization parameters are formally designated as 'regularization-optimized ANN' models, reflecting their enhanced capacity for generalization through systematic parameter adjustment. Artificial Neural Networks trained through adaptive learning processes typically incorporate hyperparameters such as learning and momentum rates, with these parameters traditionally optimized through error minimization between observed and predicted values. However, this approach differs substantially from hyperparameter-optimized ANN models in their fundamental methodology. While adaptive learning processes employ automatic parameter determination for residual minimization, hyperparameter-optimized ANNs implement a more sophisticated approach, requiring meticulous customization of network topology parameters. This optimization process demands systematic trial-and-error experimentation, with particular emphasis on two critical objectives: mitigating overfitting tendencies and preserving biological realism. The careful calibration of architectural parameters, including learning and momentum rates, represents a more rigorous and controlled approach to network optimization compared to adaptive learning methodologies. To address overfitting challenges and maintain biological realism in neural networks, various regularization optimization strategies have emerged as effective methodological approaches. These techniques include early stopping protocols based on Root Mean Square Error (RMSE) metrics, regularization implementations incorporating L1 and L2 penalty terms, and dropout mechanisms utilizing randomly excluded neural units. These methodologies collectively serve to reduce network model complexity while enhancing the robustness of neural network architectures (McCorduck, 2004; Goodfellow et al., 2016).

4. The growth laws and biological realism in tree growth

In forestry science about tree and stand growth and yield modeling studies, while the assessment of statistical prediction models such as regression analyses traditionally relies on various metrics including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), coefficient of determination (R^2), Bias, and Root Mean Square Error (RMSE), the biological coherence of these models holds paramount importance. Specifically, the predictive behavior patterns generated by these prediction models must demonstrate fundamental consistency with the inherent biological development trends and natural characteristics of the modeled attributes. As stated in many studies such as Bailey and Clutter (1974) and Cieszewski (2002), desirable characteristics of height growth curves are: (1) a sigmoidal structure (known as an "S curve"); (2) a logical behavior with a zero value of height at age zero; (3) polymorphism; (4) an asymptotic behavior; and (5) base-age invariance.

The fundamental principles of biological realism in tree growth volumetrics were initially established by Heinrich Cotta in the early nineteenth century (Clark, 1902). A primary tenet of this biological framework establishes that tree stem volume is fundamentally determined by the interaction of three key parameters: diameter at breast height (DBH), total tree height (TTH), and tree form (Avery and Burkhart, 1983). While many contemporary volume prediction systems primarily utilize DBH and TTH as independent variables for total tree volume (TTV) estimation, often excluding tree form considerations (van Laar and Akca, 1997), the underlying biological relationships remain crucial. The relationship between these parameters exhibits specific biological patterns: TTV demonstrates a positive correlation with DBH when TTH remains constant, and similarly, TTV increases with increasing TTH for constant DBH values. Significantly, these relationships

follow allometric curvilinear patterns rather than linear trajectories (Spurr, 1952; Avery and Burkhart, 1983). For hyperparametrized Deep Learning Architecture (DLA) models to gain acceptance within the forestry literature as effective prediction systems, they must demonstrate consistency with these established biological patterns. Any deviation from expected trends, such as decreases or unexpected fluctuations in TTV values at higher DBH and TTH values, would constitute a violation of biological realism, potentially compromising the model's validity and utility in forestry applications.

In addition to comparing and evaluating various models for estimating individual tree and stand characteristics according to different performance criteria (R^2 , Bias, RMSE, AIC, BIC, etc.), the assessment of prediction accuracies obtained through these prediction models is also conducted using graphical methods. In a related evaluation, Ercanli et al. (2023) presented graphs of dominant height growth predictions for five site index values (i.e., 5, 10, 15, 20, 25, and 30 m at base age 100) obtained through both ANN models and a nonlinear mixed effects model with one random parameter (Fig. 1). Upon examination of Figure 1, while biologically consistent estimates of dominant height development are observed in the left corner of the graph (Fig. 1a), the standard feed-forward ANN model - trained with an adaptive learning process without any hyperparameter or regularization parameter specifications - produced predictions that significantly violate and are highly inconsistent with growth laws and biological realism about dominant tree heights. Ercanli (2024), in a study utilizing Deep Learning Algorithm - a multilayer artificial neural network - to predict individual tree taper using stem diameters outside bark (DOB) and total tree volume (TTV), obtained results highly inconsistent with biological realistic patterns for both characteristics when using a standard DLA model based on adaptive learning (Fig. 2b and 3b). The implementation of optimized DLA architectures—specifically, a hyperparameter-optimized model with 0.8 momentum and seven hidden layers for TTV predictions, and a regularization-optimized model with 1×10^{-6} dropout ratio and three hidden layers for DOB estimations—yielded statistically robust results across both training and validation datasets while preserving biological plausibility in their predictions (Fig. 2a and 3a). The predictive outcomes generated by both hyperparameter-optimized and regularization-optimized DLA models for TTV (Fig. 2a) and DOB (Fig. 3a) demonstrate strong adherence to established biological principles governing tree volume and diameter growth patterns in dendrometric science (Avery and Burkhart, 1983; van Laar and Akca, 1997; Pretzsch, 2009).

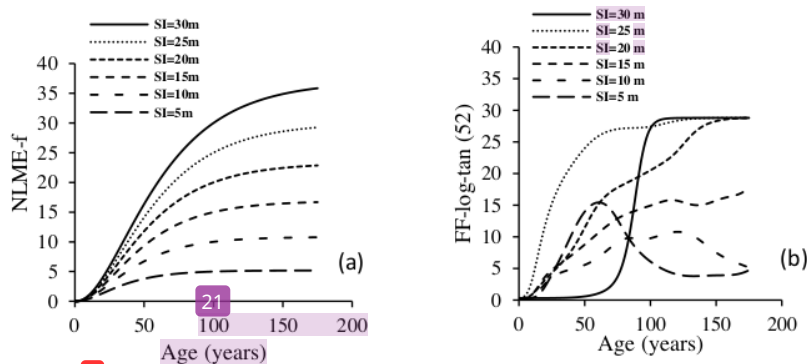


Fig. 1. Predicted site index curves for five site index values by Nonlinear mixed effect regression, feed-forward network architectures and ANN with feed forward learning-log-tan of activation functions and 52 number of neurons (Ercanli et. al. 2023)

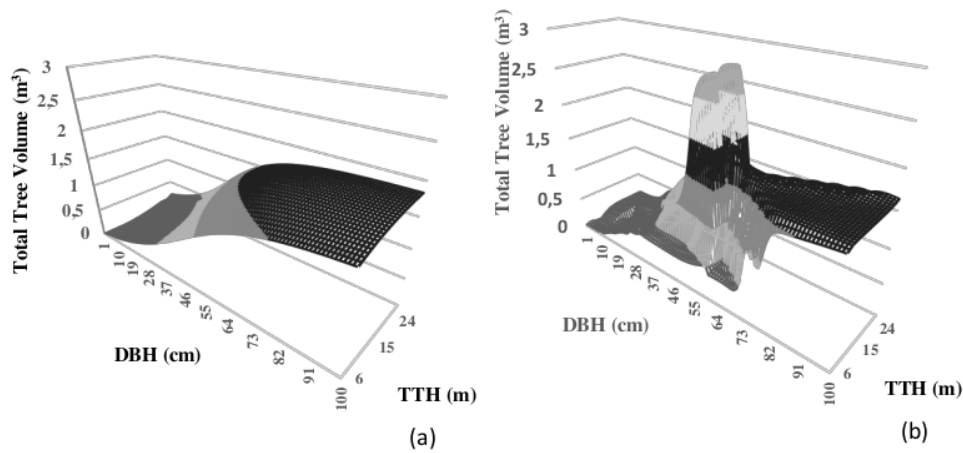


Figure 2. The change of total tree volumes predicted by the best predictive hyper-parametrized DLA (a) and the standard DLA including 10 (b) number of hidden layer and according to DBHs and Total tree height (TTH) (Ercanlı, 2024)

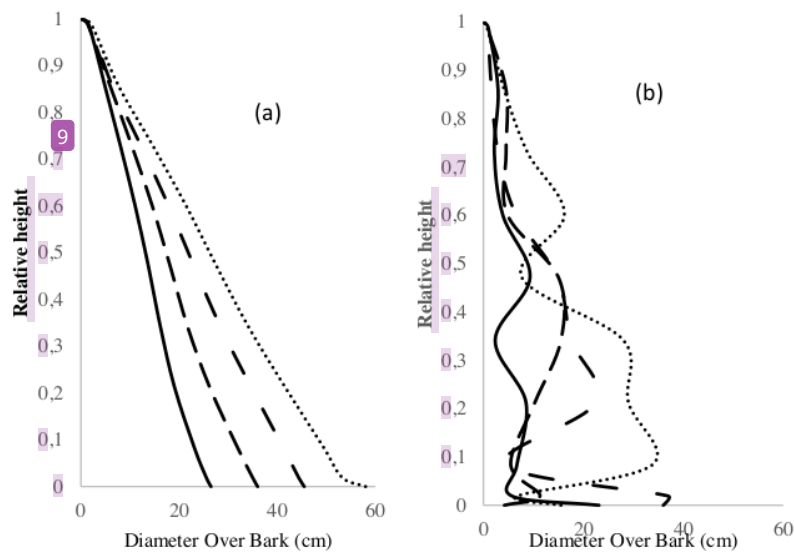


Fig. 3. The predicted stem profiles by the Fang et. al (2000)'s taper equation based on NLS (a), CAR (1) (b), the best predictive regularization-optimized DLA and the standard DLA with a 3 # hidden layer (d) (Ercanlı, 2024)

Conclusion

This investigation explores the fundamental question of whether artificial intelligence can be effectively trained to incorporate inherent biological patterns and growth laws of tree development, while providing a systematic assessment of AI model implementations in forestry applications, a

distinct branch of natural sciences. Despite artificial intelligence models demonstrating superior performance metrics compared to traditional regression models from statistical science, the evaluation of predictive models in natural sciences, particularly in forestry, extends beyond mere statistical performance criteria. While artificial intelligence models demonstrate remarkable predictive ability through their sophisticated nonlinear fitting capabilities, their training process necessitates consideration of factors beyond conventional adaptive learning approaches, which traditionally focus on minimizing the residuals between observed and predicted values. The employment of hyperparameter-optimized and regularization-optimized DLA models, trained via an innovative methodology incorporating customized network parameters, presents a significant advancement in simultaneously addressing two critical challenges in forest modeling: (i) the statistical issues of overfitting and generalization capacity, and (ii) the maintenance of biological realism in tree and stand attribute predictions. In addressing the fundamental question 'Can artificial intelligence be trained to account for the growth laws and biological patterns inherent in tree growth?', two distinct methodological approaches emerge in the implementation of AI models with DLA for forestry applications:

- (i) Adaptive learning-based AI models prone to overfitting, which demonstrate high fidelity to training data but fail to capture underlying biological relationships, essentially resulting in data memorization rather than pattern recognition;
- (ii) Advanced DLA implementations incorporating hyperparameter optimization and regularization techniques, characterized by systematic customization of network parameters to enhance model generalization and biological consistency. The optimization-based approach represents a significant advancement in elucidating the 'black-box' nature of these models, enabling the capture of intricate data relationships. Through the systematic implementation of hyperparameter optimization and regularization techniques, these advanced DLA frameworks demonstrate remarkable capacity in maintaining biological fidelity while mitigating overfitting and enhancing generalization capabilities. In this context, the Human-Centered Artificial Intelligence (HCAI) paradigm has been comprehensively conceptualized by Holzinger et al. (2022). The application of this paradigm to forest science represents a symbiotic integration of artificial and natural intelligence. This integration aims to augment, support, and optimize artificial intelligence systems, such as Artificial Neural Networks (ANN) or Deep Learning Algorithms (DLA), with human knowledge and perspective in forest growth and yield predictions. This approach facilitates a synergistic confluence of technological innovation and human experiential expertise. However, the full potential of DLA applications in forestry science remains to be fully explored as our understanding of its inherent capabilities and limitations continues to advance.

References

- Armstrong, S., Sotala, K., and O. S. Heigeartaigh. 2014. The errors, insights and lessons of famous AI predictions – and what they mean for the future. *J. Exp. Theor. Artif. Intell.* 26: 317-342.
- Ashraf, M.I., Zhao, Z., Bourque, C.P.A, MacLean, D.A., and F.R. Meng. 2013. Integrating biophysical controls in forest growth and yield predictions with artificial intelligence technology. *Can. J. For. Res.* 43: 1162-1171.
- Avery, T. and E. Burkhart. 1983. *Forest Measurement*. Third Edition. McGraw-Hill, New York. 331 p.
- Bailey, R. L. and Clutter J. L. 1974. Base-age invariant polymorphic site curves. *Forest Sci* 20: 155–159.
- Brynjolfsson, E. and T. Mitchell. 2015. What can machine learning do? Workforce implications. *Science* 358: 1530–1534.

- 2 Cieszewski, C. J. 2002. Comparing fixed and variable-base-age site equations having single versus multiple asymptotes. *Forest Sci* 48 (1): 7-23.
- 5 Jark, J.F. 1902. Volume tables and the bases on which they may be built. *Forestry* 1: 6–11.
- Diamantopoulou, M.J., Özçelik, R., Crecente-Campo, F. and Ü. Eler. 2015. Estimation of Weibull function parameters for modelling tree diameter distribution using least squares and artificial neural networks methods. *Biosyst. Eng.* 133: 33-45.
- Ercanlı, İ., Bolat, F. and H. Yavuz. 2023. A comparison of artificial neural networks and regression modeling techniques for predicting dominant heights of Oriental spruce in a mixed stand. *Forest Systems*, 32 (1).
- Ercanlı, İ. 2024. Deep learning algorithms for addressing overfitting and biological realism in tree taper and volume predictions, *Can. J. For. Res.* First: 1–19 (2024)
- 26 Goodfellow, I., Bengio, Y. and A. Courville. 2016. *Deep learning*. MIT press.
- 3 Holzinger, A., Saranti, A., Angerschmid, A., Retzlaff, C. O., Gronauer, A., Pejakovic, V., Medel-Jimenez, F., Krexner, T., Gollob, C., K. Stampfer, K. 2022. “Digital transformation in smart farm and forest operations needs human-centered AI: Challenges and future directions.” *Sensors*, 22(8), 3043.
- 15 Lei, Y. and B.R. Parresol. 2001. Remarks on heightdiameter modelling. Res. Pap. SRS-10. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 6p
- 13 Levens, R. 1966. The strategy of model building in population biology. *Am. Sci.* 54(4), 421-431.
- 7 McCorduck, P. 2004. *Machines who think: A personal inquiry into the history and prospects of artificial intelligence* (2nd ed.). CRC Press. 598 p.
- 23 Nilsson, N. J. 2014. Understanding beliefs. The MIT Press Essential Knowledge series. 168 p.
- 4 Özçelik, R., Diamantopoulou, M.J., Brooks, J.R. and H.V. Wiant Jr. 2010. Estimating tree bole volume using artificial neural network models for four species in Turkey. *J. Environ. Manage.* 91: 742-753.
- 16 Russell, S., Hauert, S., Altman, R. and M. Veloso. 2015. Ethics of artificial intelligence. *Nature* 521: 415–416.
- 20 Surr, S.H. 1952. *Forest inventory*. New York: Ronald Press Co. 476 p.
- 14 Tideo, M. and L. Floridi. 2018. How AI can be a force for good. *Science* 361: 751–752.
- 22 Turing, A., 1950. Computing Machinery and Intelligence. *Mind* 59 (236): 433–60.
- 17 Van Laar A. and A. Akça. 2007. *Forest mensuration*. Springer, Dordrecht, Netherlands, 383 p.

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