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Enhancing Bed Alignment and Reducing Calibration Time in 3D Printers Using Auto Leveling with PI Control

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Abstract

Manual bed leveling in fused deposition modeling (FDM) 3D printers is operator-dependent and often produces an uneven nozzle-bed gap, which reduces first-layer adhesion and dimensional repeatability. This study developed a retrofittable auto leveling system based on Proportional-Integral (PI) control for a Cartesian 3D Touch 3D printer at Politeknik ATMI Surakarta. The system combines a 3D Touch probe, three NEMA 17 motorized bed supports, one fixed-jaw reference, DRV8825 drivers, an Arduino Mega 2560, and a Raspberry Pi 4B to measure the bed at nine probing points and physically correct the bed height. Bed deviation was defined as the difference between the maximum and minimum measured height at the bed support reference points. Five Kp-Ki combinations were tested using a 0.05 mm tolerance. The best response was obtained at Kp = 1.0 and Ki = 0.03, completing calibration in 223 s with four iterations and a 0.016 mm deviation. Across five trials, auto leveling reduced the average calibration time from 594.4 s to 255.4 s (57.0%) and reduced the average bed deviation from 0.2228 mm to 0.0232 mm (89.6%) compared with manual leveling. ASTM D638 Type I print validation showed 90% successful squareness. The results demonstrate that PI-controlled physical bed alignment can improve calibration efficiency, repeatability, and first-layer reliability in low-cost FDM printers.

Keywords: *3D printer; auto leveling; bed alignment; fused deposition modeling; PI control*

Abstrak

Leveling bed manual pada printer 3D *fused deposition modeling* (FDM) sangat bergantung pada operator dan sering menghasilkan jarak *nozzle-bed* yang tidak seragam, sehingga menurunkan daya rekat lapisan pertama dan keterulangan dimensi. Penelitian ini mengembangkan sistem auto leveling berbasis kendali Proporsional-Integral (PI) yang dapat dipasang pada printer 3D *Cartesian* 3D *Touch* di Politeknik ATMI Surakarta. Sistem ini menggabungkan sensor 3D *Touch probe*, tiga penyangga bed bermotor NEMA 17, satu referensi *fixed-jaw*, *driver* DRV8825, Arduino Mega 2560, dan Raspberry Pi 4B untuk mengukur bed pada sembilan titik *probing* dan mengoreksi ketinggian *bed* secara mekanis. Deviasi *bed* didefinisikan sebagai selisih antara nilai ketinggian maksimum dan minimum pada titik referensi penyangga bed. Lima kombinasi Kp-Ki diuji dengan toleransi 0,05 mm. Respons terbaik diperoleh pada Kp = 1,0 dan Ki = 0,03, dengan waktu kalibrasi 223 s, empat iterasi, dan deviasi 0,016 mm. Dalam lima pengujian, *auto leveling* menurunkan rata-rata waktu kalibrasi dari 594,4 s menjadi 255,4 s (57,0%) dan menurunkan rata-rata deviasi *bed* dari 0,2228 mm menjadi 0,0232 mm (89,6%) dibandingkan leveling manual. Validasi cetak spesimen ASTM D638 Type I menunjukkan 90% keberhasilan *squareness*. Hasil ini menunjukkan bahwa penyelarasan *bed* secara mekanis dengan kendali PI dapat meningkatkan efisiensi kalibrasi, keterulangan, dan keandalan lapisan pertama pada printer FDM berbiaya rendah.

Kata kunci: 3D printer; *auto leveling*; *alignment bed*; *fused deposition modeling*; kendali PI

1. Introduction

Additive manufacturing, especially fused deposition modeling (FDM) or fused filament fabrication (FFF), has become a widely used method for rapid prototyping and functional polymer parts because it can fabricate complex geometries with relatively low equipment cost [1-2]. The quality of FDM parts, however, is strongly influenced by material behavior, rheological properties, process parameters, and printer setup. Reviews of FDM/FFF materials and PLA-based printing emphasize the roles of filament processing, thermoplastic rheology, and polymer behavior during extrusion [3-6].

Process-parameter studies further show that layer height, extrusion temperature, print speed, infill pattern, material type, filament flow consistency, and build-platform condition affect dimensional accuracy and mechanical performance [7-10]. Therefore, improving the stability of the printer setup is an important requirement before optimizing higher-level process parameters.

One setup variable that directly affects print reliability is the nozzle-bed distance during the first layer. If the bed is not parallel to the nozzle motion plane, the first layer can be over-compressed at one side and under-compressed at another side. A gap that is too small may block the nozzle or scratch the build surface, while a gap that is too large can reduce adhesion and cause warping or print failure. Previous studies show that bed temperature, thermal deformation, polymer dimensional stability, and first-layer adhesion influence warpage and printed-part accuracy [11-14]. Automatic bed leveling has also been investigated using load-cell contact detection, optical leveling, probe-based surface mapping, robotic printing platforms, and 3D Touch probe mechanisms [15-18]. These studies confirm the importance of bed flatness and nozzle-bed gap consistency, but many systems focus on surface measurement or firmware compensation rather than physical bed correction using independently actuated supports.

Recent FFF research has also moved toward in-process measurement, condition monitoring, defect detection, and closed-loop control. Closed-loop filament feed control can reduce filament transport error and improve print density [19]. Image-based closed-loop correction, machine-learning defect detection, and feedback-based quality control have been used to detect or correct extrusion-related defects during printing [20-23]. Recent reviews and measurement studies also show that monitoring data from machine condition, temperature, current, extruder pressure, and embedded/additively manufactured sensors can support more reliable and adaptive FFF operation [24-28]. Although these studies demonstrate the value of feedback control in FFF, they mainly address extrusion flow, defect diagnosis, sensor fabrication, and process parameter correction. The controller behavior and quantitative gain selection for a low-cost physical bed-alignment mechanism remain less discussed.

The research gap addressed in this study is the need for a low-cost, retrofittable auto leveling system that not only measures bed height but also physically aligns the bed using feedback control. A previous 3D Touch-based auto-level system demonstrated the feasibility of probe-assisted bed adjustment, but further analysis is needed on PI gain selection, convergence behavior, measurement of deviation, and quantitative comparison with manual calibration [18]. Therefore, this study contributes: (1) a three-motor bed-support mechanism with one fixed-jaw reference; (2) a PI control algorithm for minimizing bed height error; (3) a clear definition of bed deviation and leveling time measurement; and (4) an experimental comparison of calibration time, bed deviation, and print squareness between manual leveling and auto leveling. The novelty of this work is positioned between auto bed-leveling studies that emphasize measurement/compensation [15]-[18] and recent closed-loop or monitoring studies that focus mainly on extrusion, defect detection, and process quality [19]-[28], by focusing specifically on physical bed-plane correction before printing.

2. Material and Method

This study used an experimental development method supported by the ADDIE framework, consisting of Analyze, Design, Develop, Implement, and Evaluate stages. The experiment was conducted on a Cartesian-type 3D Touch 3D printer that was modified with a PI-controlled auto leveling system. The machine dimensions were 515 mm x 515 mm x 598 mm, with a print bed size of 235 mm x 235 mm. The work was conducted at the Mechatronics Engineering Technology Laboratory, Politeknik ATMI Surakarta.

The main hardware consisted of an Arduino Mega 2560, Raspberry Pi 4B, SKR 1.4 controller board, 3D Touch probe sensor, NEMA 17 stepper motors, DRV8825 stepper drivers, and a coupling transmission mechanism for bed support adjustment. The software consisted of Arduino IDE, Thonny Python, and Marlin 2.1.2.5 firmware. PLA+ filament was used for print validation.

2.1 Research Stages

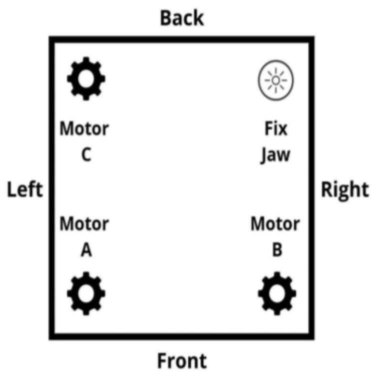
The research stages were carried out using the ADDIE method, which consists of:

1. Analyze: The problem of manual bed leveling was identified by observing calibration time, operator dependency, and inconsistent bed flatness. Literature related to FDM printing, bed leveling, and closed-loop control was reviewed to define the research gap.
2. Design: The auto leveling system was designed by determining the 3D Touch probe position, three motorized bed support points, one fixed-jaw reference point, PI control logic, and communication between the Raspberry Pi, printer controller, and Arduino Mega 2560.
3. Develop: The system was developed by installing the 3D Touch probe on the nozzle carriage, adding the three motorized bed supports, connecting the drivers and controllers, and programming the PI control routine for bed height correction.
4. Implement: The system was tested under real printer operating conditions. Leveling time, bed deviation, number of iterations, and printed specimen squareness were recorded.
5. Evaluate: The auto leveling results were compared with manual leveling results. The Kp and Ki values were varied to determine the most efficient combination that could satisfy the 0.05 mm bed-deviation tolerance.

2.2 Auto Leveling Mechanism and PI Control

The auto leveling mechanism used three motorized bed supports, named Motor A, Motor B, and Motor C, and one fixed-jaw point as the height reference. The 3D Touch probe measured the bed surface using a nine-point probing routine. The measured heights were then used to estimate the height of the three motorized supports and the fixed-jaw reference point. This approach differs from firmware-only compensation because the bed-support positions are physically corrected before the print begins, which is consistent with the practical need for stable first-layer geometry reported in previous auto-leveling studies [15]-[18]. The configuration of the 3D printer and bed support arrangement is shown in Figure 1.

(a)



(b)

Figure 1. (a) 3D Touch 3D printer machine, (b) bed support arrangement used by the auto leveling mechanism

For each leveling iteration k, the fixed-jaw height was used as the reference height h_ref(k). The height error of each motorized support i was calculated as Equation (1).

$$e\_i(k) = h\_ref(k) - h\_i(k), \text{ for } i = A, B, C \tag{1}$$

The PI controller output was calculated using Equation (2).

$$u\_i(k) = Kp\ e\_i(k) + Ki\ sum(e\_i(k)) \tag{2}$$

Where u_i(k) is the required correction of the bed support, Kp is the proportional gain, and Ki is the integral gain. The proportional term corrected the current height error, while the integral term reduced the remaining steady-state error caused by mechanical backlash, friction, and small residual offsets. This feedback principle is consistent with recent FFF closed-loop studies showing that measured process errors should be converted into corrective commands instead of being corrected only by trial-and-error setup [19-20]. After the correction command was sent to the stepper motor, the probing cycle was repeated until the bed deviation satisfied the tolerance requirement.

2.3 Deviation and Leveling Time Measurement

Bed deviation was explicitly defined as the difference between the maximum and minimum height measured at the four bed support reference points (Equation (3)).

$$D = h\_max - h\_min \tag{3}$$

Where h_max is the highest measured support height and h_min is the lowest measured support height. A leveling result was accepted when D <= 0.05 mm. The auto leveling time was measured from the start of the probing command until the controller stopped because the deviation was within tolerance. Manual leveling time was measured from the start of knob adjustment until the operator confirmed the nozzle-bed gap at the reference points. The number of loops was counted from each complete cycle of probing, error calculation, motor correction, and re-probing. If the sixth loop was reached without satisfying the tolerance, the gain combination was considered inefficient for the present mechanism. This measurement definition was used to make the present results comparable with bed-leveling and FFF metrology studies that report probing time, surface deviation, or dimensional error as performance indicators [15;17;25;40].

2.4 Testing Procedure

Two groups of tests were conducted. First, flatness testing was performed to evaluate the effect of Kp and Ki on leveling time, deviation, and number of loops. Five gain combinations were tested, and the best combination was selected based on the fastest time, the fewest loops, and deviation below 0.05 mm. Second, print validation was performed using ASTM D638 Type I specimens. The specimen dimensions and vertical flatness were measured using visual inspection, an L-square, a dial indicator, a vernier caliper, and a micrometer screw gauge. Dimensional measurement and geometric validation are commonly used in FDM optimization studies because process parameters, temperature history, material shrinkage, and interlayer bonding can alter the final size and shape of printed polymer parts [29-39]. The ASTM D638 specimen geometry is shown in Figure 2.

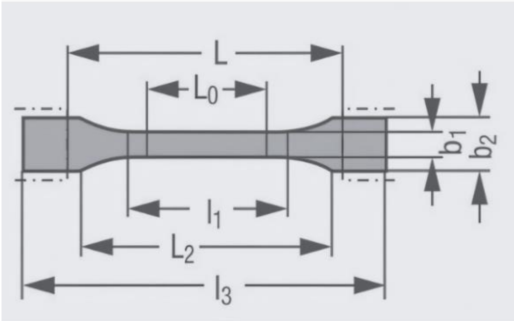


Figure 2. ASTM D638 Type I specimen geometry used for print validation

3. Results and Discussion

The results are discussed in three parts: PI gain testing, comparison between auto leveling and manual leveling, and ASTM D638 Type I print validation. The discussion emphasizes controller behavior, measurement interpretation, comparison with related auto-leveling systems, and the relationship between bed alignment, first-layer reliability, and dimensional accuracy.

3.1 Effect of Kp and Ki on Auto Leveling Response

The PI gain test evaluated how Kp and Ki affected convergence speed and bed deviation. In feedback-controlled FFF systems, controller tuning must balance final error, response time, and stability because excessive correction can increase repeated adjustment cycles, while insufficient correction leaves residual error [19-22]. The test results are summarized in Table 1. Compared with the original manuscript, the table was simplified to focus on the variables needed to justify the controller selection: gain values, loops, time, deviation, and decision.

Table 1. Effect of PI gain variation on leveling performance

Test Number	Kp	Ki	Motor A (mm)	Motor B (mm)	Motor C (mm)	Fix Jaw (mm)	Looping	Estimated Time	Deviation (mm) Max - Min	Decision
1	1	0.03	0.285	0.278	0.273	0.289	4	3 Min 43 Sec	0.016	Selected
2	1.2	0.03	0.679	0.677	0.672	0.676	5	4 Min 23 Sec	0.007	Accurate but slower
3	0.8	0.03	0.665	0.682	0.665	0.687	5	4 Min 27 Sec	0.022	Accepted but slower
4	1.1	0.02	0.317	0.339	0.299	0.321	5	4 Min 24 Sec	0.04	Accepted but near tolerance
5	0.9	0.02	0.561	0.531	0.562	0.532	5	4 Min 20Sec	0.031	Accepted but slower

Kp = 1.0 and Ki = 0.03 were selected because this combination achieved the fastest convergence, the fewest loops, and a deviation far below the 0.05 mm tolerance. Although Kp = 1.2 and Ki = 0.03 produced the smallest final deviation (0.007 mm), it required five loops and 263 s. This indicates that a larger proportional gain increased correction aggressiveness but did not reduce total calibration time on this mechanical system. Kp = 0.8 and Ki = 0.03 converged more slowly because the proportional correction was smaller, while Ki = 0.02 combinations also required five loops and produced larger residual deviations. Therefore, the selected gains represent the best compromise between speed and accuracy. This interpretation follows the same control logic used in FFF closed-loop studies, where controller gains must reduce measured error without causing unnecessary repeated correction or instability [19-25].

The controller's behavior can be interpreted as follows. The proportional term quickly moved each motorized support toward the fixed-jaw reference, while the integral term compensated for remaining offsets that were not eliminated by the proportional action alone. A very small integral contribution slowed the removal of residual error, whereas a higher proportional value increased the risk of repeated correction and re-probing. For the present bed mechanism, Kp = 1.0 and Ki = 0.03 were sufficient to reach stable alignment without excessive oscillatory correction. This result supports the broader FFF control perspective that feedback should be tuned based on both final accuracy and convergence behavior, not only the smallest final error [19]-[25].

3.2 Comparison of Auto Leveling with Manual Leveling

The manual leveling test involved adjusting the bed height with hand knobs at the four corners until the nozzle maintained a consistent distance from the surface, verified by a sensor. This served as a reference to compare the print surface accuracy and consistency with the auto leveling system, as shown in Figure 3 which shows the leveling time for each test, and Figure 4 shows the corresponding bed deviation.

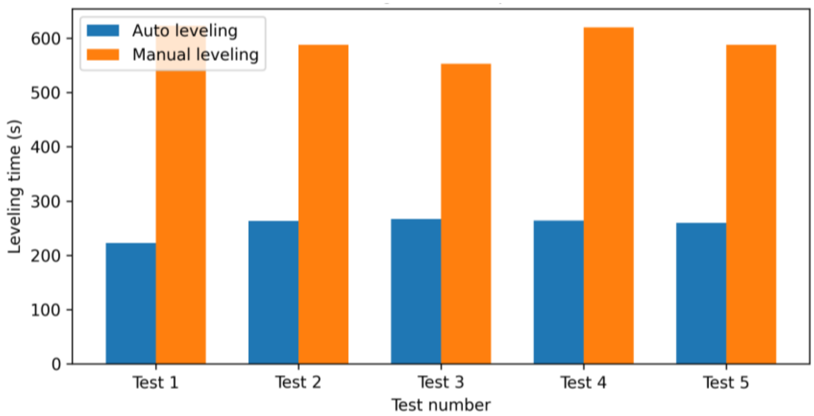


Figure 3. Leveling time comparison between auto leveling and manual leveling

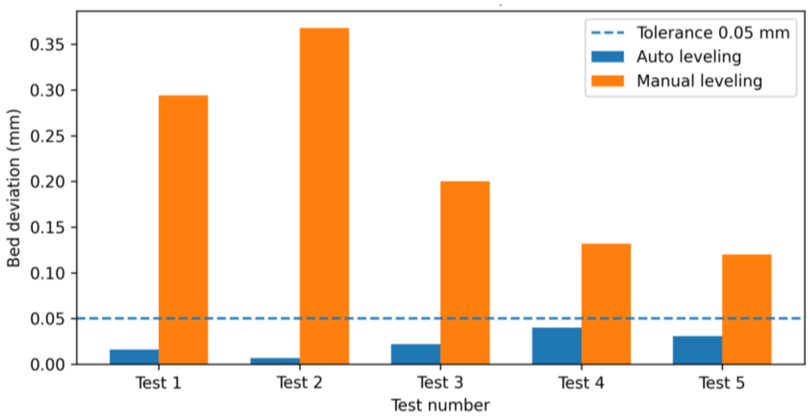


Figure 4. Bed deviation comparison between auto leveling and manual leveling

The auto leveling process required 223-267 s, with an average of 255.4 s. Manual leveling required 553-623 s, with an average of 594.4 s. Thus, the proposed system reduced the average calibration time by 57.0%. The improvement was mainly obtained because the controller corrected the three bed supports based on measured error rather than repeated manual trial-and-error adjustment. This result supports previous findings that automatic bed measurement can reduce calibration effort and improve operation efficiency, while the present system extends the concept by mechanically correcting the bed support using PI control [15-18].

The bed deviation also improved substantially. Auto leveling produced deviations of 0.007-0.040 mm, with an average of 0.0232 mm, which was consistently below the 0.05 mm tolerance. Manual leveling produced deviations of 0.120-0.368 mm, with an average of 0.2228 mm. Therefore, auto leveling reduced the average deviation by 89.6% and made the bed approximately 9.6 times more uniform than manual leveling. This result confirms that the proposed PI-controlled mechanism improves not only speed but also repeatability. Improved repeatability is important because FDM part quality is sensitive to first-layer adhesion, bed temperature, dimensional stability, residual strain, and interlayer bonding conditions [11-14; 35-39].

Compared with load-cell-based automatic bed leveling that uses nozzle contact detection and firmware compensation [15], the present system requires a longer calibration time because it physically moves three bed supports and repeats probing until the mechanical bed plane is aligned. Compared with robotic print-bed leveling that uses grid-based probing for large workspaces [17], the present system is intended for a compact educational FDM printer and uses a low-cost 3D Touch probe with three actuated supports. The advantage of this approach is that the bed itself is corrected before printing, reducing dependence on continuous Z-axis compensation during the first layer. This is important for low-cost or educational printers where a simple mechanical retrofit is preferred.

3.3 ASTM D638 Type I Print Validation

After auto leveling, ASTM D638 Type I specimens were printed vertically to evaluate whether bed alignment could support consistent specimen geometry and squareness. The table was simplified from the original version by reporting the maximum vertical flatness value at each specimen rather than listing bottom, middle, and top values separately. Vertical printing was selected as a sensitive validation condition because printed specimens are affected by layer bonding, void architecture, temperature field, residual strain, and interlayer adhesion [35-39]. The final calibration values were derived from ten test trials, as detailed in Table 4.

Table 4. List of ASTM D638 Type 1 dimensions and vertical flatness test

Test Number	Dimensions				Vertical Flatness			Squareness
	L3 $\geq$ 165 mm	b2 19±6.4 mm	b1 13±0.5 mm	h 3.2±0.4 mm	Bottom	Middle	Top	
1	169	19.2	13.02	3.24	0	0.1	0.24	Not OK
2	168.3	19.15	13.05	3.2	0	0.01	0.03	OK
3	169	19.2	13	3.2	0	0.05	0.06	OK
4	168	19.15	13	3.22	0	0.01	0.04	OK
5	167	19.2	13.02	3.24	0	0	0.05	OK
6	167.5	19.3	13.04	3.22	0	0.02	0.03	OK
7	168	19.1	13	3.2	0	0.01	0.04	OK

8	168	19.3	13.02	3.2	0	0.03	0.06	OK
9	166	19.25	13.02	3.24	0	0.01	0.03	OK
10	167	19.1	13.05	3.2	0	0.02	0.02	OK

Table 4 shows that 9 of 10 specimens met the squareness criterion, giving a 90% success rate. Most dimensional values were within the expected ASTM D638 Type I range used in this study: L3 >= 165 mm, b2 = 19 +/- 6.4 mm, b1 = 13 +/- 0.5 mm, and h = 3.2 +/- 0.4 mm. The first specimen was not square and showed the highest maximum vertical flatness value (0.24 mm). This result is likely related to the initial print condition and the vertical printing orientation, which is more sensitive to first-layer adhesion, slenderness, interlayer bonding, and local extrusion stability than horizontal printing [11-12; 35-36].

The validation also indicates that bed leveling improves the initial geometric condition but does not eliminate all dimensional errors. FDM dimensional accuracy is still affected by layer height, material shrinkage, cooling condition, extrusion consistency, filament properties, build orientation, infill strategy, and slicing parameters. Recent optimization and dimensional stability studies report that parameter selection strongly affects dimensional accuracy and geometry retention [29-34], while interlayer bonding, void formation, thermal field, residual strain, and temperature-dependent adhesion also influence printed-part integrity [35-39]. Therefore, the proposed auto leveling system should be interpreted as a bed-alignment improvement that supports print reliability, not as a complete replacement for process-parameter optimization.

3.3 Scientific Contribution, Limitations, and Future Development

The scientific contribution of this study is the experimental demonstration of a PI-controlled physical bed-alignment mechanism for a low-cost FDM printer. Unlike probe-only bed mapping, the proposed system adjusts the bed supports mechanically before printing. Unlike recent closed-loop FFF studies that focus on filament feed, image-based fault correction, condition monitoring, sensor-based diagnostics, or machine-learning defect feedback [19-28], this study focuses on the first-layer geometric condition by controlling bed support height. This contribution also complements dimensional qualification research in material extrusion, where geometric alignment and measurement are important for achieving reliable printed parts [40].

The main limitation is that the system was evaluated on one printer platform, one bed size, and PLA+ material. The gain search was limited to five Kp-Ki combinations, so the selected gain should be considered optimal for the tested mechanism rather than universally optimal for all FDM printers. Long-term repeatability, thermal drift, bed warpage at elevated bed temperature, motor backlash over prolonged use, and tensile strength of the ASTM specimens were not evaluated in this study.

Future research should evaluate adaptive PI or PID control, automatic gain tuning, backlash compensation, and integration with first-layer image monitoring. Testing should also be extended to different filaments, nozzle sizes, bed temperatures, and printer platforms. A longer durability test is recommended to determine whether the system can maintain calibration accuracy after repeated heating and printing cycles. Future development can also integrate machine vision, current monitoring, extruder-pressure measurement, sensorized monitoring, thermal simulation, and 3D scanning to create a more complete closed-loop calibration and quality-control system [20-28; 37-40].

4. Conclusion

This study developed and evaluated a PI-controlled auto leveling system for improving bed alignment and reducing calibration time in a Cartesian FDM 3D printer. The best gain combination was Kp = 1.0 and Ki = 0.03, which completed calibration in 223 s with four loops and a 0.016 mm deviation. Across five trials, auto leveling reduced average calibration time from 594.4 s to 255.4 s, equivalent to a 57.0% reduction. Average bed deviation was reduced from 0.2228 mm to 0.0232 mm, equivalent to an 89.6% reduction and consistently below the 0.05 mm tolerance.

The main contribution of this research is a low-cost, retrofittable, mechanically correcting auto leveling system that combines a 3D Touch probe, three motorized bed supports, one fixed reference, and PI control. The ASTM D638 Type I print validation showed a 90% squareness success rate, confirming that the improved bed alignment supports better first-layer reliability and print consistency.

The limitations of this study are the use of a single printer platform, limited gain combinations, one filament type, and the absence of long-term thermal and mechanical durability tests. Future work should investigate adaptive controller tuning, backlash compensation, temperature-related bed deformation, multiple materials, first-layer camera feedback, and long-term repeatability under repeated printing cycles.

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