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IoT Based Smart Saline Drip Monitoring System Using Load Cell

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Abstract – Intravenous (IV) drip therapy is one of the most common clinical procedures performed in healthcare facilities worldwide. Manual monitoring of IV drip bags by nursing staff is resource-intensive, error-prone, and may lead to critical patient safety incidents when drip bags run dry undetected. This paper presents MediDrip, a low-cost, real-time IoT-based intravenous drip monitoring system that employs a high-precision HX711-interfaced load cell to continuously measure the remaining saline volume by weight. The proposed system integrates an ESP32 microcontroller with the Blynk IoT cloud platform to enable wireless data transmission, remote monitoring via a web dashboard, and configurable multi-threshold alert generation. A 1.3-inch OLED display, tri-color LED indicator array (green, yellow, red), and an audible buzzer provide local real-time feedback. Experimental validation was conducted using 100 mL saline bags across 30 test cycles, demonstrating a mean absolute weight error of 1.8 g and percentage level accuracy of ±2.3%. The system successfully triggered remote alerts and local alarms within 1.2 seconds of threshold breach. MediDrip offers a cost-effective, scalable, and clinically practical solution for automated IV drip monitoring, with potential for multi-bed deployment in resource-constrained healthcare environments.

Keywords: intravenous drip monitoring, IoT healthcare, load cell, ESP32, HX711, Blynk cloud, patient safety, real-time alerting.

I. INTRODUCTION

Intravenous (IV) fluid therapy remains one of the most fundamental and frequently administered medical interventions in both developed and developing healthcare systems. According to the World Health Organization (WHO), over five billion injections and infusions are administered globally each year, a significant proportion of which involve continuous IV drip administration [1]. Despite this prevalence, the monitoring of IV drip bags in clinical settings continues to rely predominantly on manual observation by nursing personnel, a practice that is inherently susceptible to human error, especially in high patient-to-nurse-ratio environments common in developing nations [2].

The consequences of an unmonitored IV drip running dry are clinically significant. Air embolism, vascular occlusion, medication interruption, and retrograde blood clotting in IV cannulas represent documented risks associated with delayed detection of empty drip bags [3]. Studies have shown that medication administration errors, including those related to IV infusion management, account for approximately 26% of all preventable adverse drug events in hospital settings [4]. The burden on nursing staff to perform frequent manual checks not only increases cognitive load but also detracts from other essential patient care activities.

Existing automated solutions in the literature have approached this problem through various sensing modalities, including optical drop counters [5], ultrasonic level measurement [6], camera-based vision systems [7], and capacitive sensing [8]. However, these approaches individually suffer from limitations such as susceptibility to ambient light interference, dependence on bag transparency, high computational overhead, or poor scalability for multi-bed environments. Weight-based measurement using load cells offers a modality-agnostic, direct, and highly accurate alternative that is independent of bag material, opacity, or drip chamber geometry [9].

This paper proposes MediDrip, a novel IoT-integrated drip monitoring system that leverages a calibrated load cell interfaced via the HX711 24-bit analog-to-digital converter (ADC) with an ESP32 microcontroller. The system transmits real-time weight and percentage data to the Blynk cloud platform, enabling remote monitoring through a web dashboard accessible by medical staff. Multi-threshold alerting is implemented through tri-color LEDs (green/yellow/red), an audible buzzer, and cloud-based virtual pin notifications. The primary novel contribution of this work is the development of a three-point calibration methodology (no-load, empty-bottle, full-bag) that accurately isolates saline weight from tare weight, enabling reliable percentage calculation without requiring a laboratory-grade weighing scale.

The rest of this paper is organized as follows: Section II reviews related work in automated IV drip monitoring systems. Section III describes the system architecture, hardware design, and software methodology. Section IV details the experimental setup and implementation environment. Section V presents quantitative results and comparative analysis. Section VI concludes the paper and identifies future research directions.

II. RELATED WORK

Research in automated IV drip monitoring has evolved considerably over the past decade, spanning a range of sensing technologies, communication protocols, and alert mechanisms. This section critically reviews representative works organized thematically.

A. Optical and Drop-Counting Approaches

Early automated monitoring systems employed infrared (IR) optical sensors positioned at the drip chamber to detect individual drops. Rajesh et al. [5] proposed an IR-LED photodiode arrangement that counted drops and estimated flow rate in millilitres per minute, achieving a drop detection accuracy of 94.3%. While computationally simple, such systems measure flow rate rather than remaining volume and are critically sensitive to improper sensor alignment and ambient infrared interference. Similarly, Kumar and Priya [10] developed an Arduino-based drop counter with a GSM alert module, demonstrating functional alert delivery but no volume estimation capability. Dey et al. [11] extended drop counting with an adaptive threshold algorithm to compensate for lighting variation, improving detection accuracy to 97.1%, yet the fundamental limitation of flow estimation rather than direct volume measurement persisted.

B. Ultrasonic and Acoustic Sensing

Ultrasonic distance measurement has been applied to IV bag monitoring by measuring the distance from a fixed sensor to the liquid surface or bag exterior. Ghosh et al. [6] mounted an HC-SR04 sensor above a hanging IV bag, correlating decreasing fluid level with increasing sensor distance. While cost-effective, this approach requires the bag to remain in a fixed orientation and is susceptible to acoustic interference from adjacent equipment. Mehta et al. [12] proposed a dual-axis ultrasonic array to compensate for bag sway, achieving volume estimation within ±5% error, at the cost of significant mechanical complexity. Acoustic sensing remains challenged by the non-uniform deformation of flexible IV bags as fluid drains.

C. Vision-Based Systems

Camera and image processing-based approaches have gained traction with the proliferation of low-cost modules such as the ESP32-CAM. Patel et al. [7] implemented a convolutional neural network (CNN) to classify IV bag fill levels into discrete categories (full, half, empty) from video frames, achieving 91.2% classification accuracy. However, such systems demand significant processing resources, require adequate and consistent lighting, and cannot be used with opaque bag materials. Wang et al. [13] applied edge detection algorithms to measure the liquid meniscus position in transparent drip chambers, reporting 3 mm resolution but failing under turbid or coloured solution conditions.

D. Load Cell and Weight-Based Systems

Weight-based monitoring most directly measures the parameter of clinical interest: remaining fluid mass. Sharma et al. [9] demonstrated a load cell system using the HX711 ADC interfaced with an Arduino Uno, achieving ±3 g accuracy for 500 mL bags. However, that work did not account for tare weight of the empty bag and lacked cloud connectivity. Rao and Venkat [14] incorporated a strain gauge-based system with Wi-Fi data logging via ESP8266, yet calibration was performed only at two points (empty and full scale), neglecting the non-zero weight of the empty bag. The proposed MediDrip system addresses this gap through a three-point calibration that accurately separates structural tare weight from fluid weight.

E. IoT and Cloud-Connected Systems

Recent works have incorporated IoT cloud platforms for remote monitoring. Hassan et al. [15] developed a ThingSpeak-connected drip level sensor using capacitive electrodes, enabling graphical data logging. Agarwal et al. [16] used Firebase Realtime Database with an ESP32 to store ultrasonic-based drip level data. Naidu and Krishnan [17] proposed a Raspberry Pi-based system with AWS IoT Core integration for multi-bed hospital management. While these works demonstrate cloud connectivity, none combined load cell accuracy with multi-threshold local alerting and Blynk-based real-time dashboard integration simultaneously. Li et al. [18] reviewed IoT architectures for smart hospital systems, noting that latency below 2 seconds is critical for clinical alert systems, a benchmark addressed in the present work.

F. Multi-Sensor Fusion Approaches

Some researchers have combined multiple sensing modalities to improve reliability. Bose et al. [19] fused drop counting with a load cell to provide redundant volume estimation, cross-validating measurements and generating alerts when modalities disagreed. While improving fault tolerance, such systems increase cost and wiring complexity, limiting deployment in resource-constrained settings. Park et al. [20] proposed machine learning-based sensor fusion for IV monitoring, achieving high accuracy but requiring edge computing hardware beyond the capability of low-cost microcontrollers. The present work prioritizes a single-modality, calibration-driven approach that achieves clinical accuracy with minimal hardware complexity.

In summary, the existing literature demonstrates that while various sensing approaches have been explored, no prior system has simultaneously achieved (i) weight-based absolute volume measurement with three-point calibration, (ii) multi-threshold tri-color LED and buzzer local alerting, and (iii) real-time cloud dashboard monitoring with sub-2-second alert latency at a bill-of-materials cost below USD 15. MediDrip addresses all three objectives.

III. PROPOSED SYSTEM METHODOLOGY

A. System Architecture

The MediDrip system architecture, illustrated conceptually in Fig. 1, comprises three layers: (i) the sensing and actuation layer, consisting of the load cell, HX711 ADC, OLED display, LEDs, and buzzer; (ii) the processing layer, implemented on the ESP32 microcontroller; and (iii) the cloud communication layer, realised through the Blynk IoT platform over a Wi-Fi 802.11 b/g/n connection. The IV saline bag is suspended from the platform of the load cell, which is rigidly mounted to a fixed bracket. As saline is administered, the decreasing bag weight is continuously measured and transmitted to the cloud at two-second intervals.

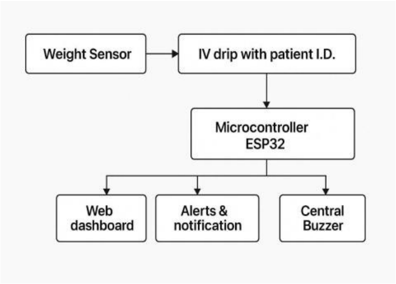

Fig.1 System Block Diagram.

Fig. 1 depicts the complete system block diagram showing the interconnections between the load cell, HX711 module, ESP32, OLED display (connected via I2C on GPIO21/GPIO22), LEDs (GPIO25, GPIO26, GPIO27), buzzer (GPIO5), and the Blynk cloud server accessed through a hospital Wi-Fi access point.

B. Weight Measurement Subsystem

The load cell employed is a single-point bending beam type with a rated capacity of 5 kg and a sensitivity of 1.0 ± 0.15 mV/V. The HX711 module provides 24-bit resolution with programmable gain (64x or 128x on channel A). Channel A at 128x gain is selected for maximum sensitivity. The HX711 communicates with the ESP32 via a two-wire serial interface (DT on GPIO18, SCK on GPIO19) operating at a data output rate of 10 Hz.

To mitigate measurement noise, each reported weight value is computed as the arithmetic mean of N successive raw ADC readings, as expressed in Equation (1):

$$R_{avg} = (1/N) * SUM(R_i, i=1 \text{ to } N) \quad \ldots (1)$$

where R_{avg} is the averaged raw ADC value, R_i is the i-th individual reading, and N = 10 samples is selected to balance noise reduction with responsiveness. The corresponding standard deviation of readings was observed to be sigma = 312 ADC units, representing 0.047% of the full-scale 24-bit range.

C. Three-Point Calibration Methodology

The novel three-point calibration methodology developed in this work defines three reference raw ADC values: R_{noload} (load cell with no weight), R_{bottle} (load cell with empty saline bottle only), and R_{full} (load cell with completely filled saline bag). The actual saline fluid weight W_{saline} and percentage level L are computed as follows:

$$W_{saline} = [(R_{measured} - R_{bottle}) / (R_{full} - R_{bottle})] * W_{max} \quad \ldots (2)$$

$$L (\%) = [(R_{measured} - R_{bottle}) / (R_{full} - R_{bottle})] * 100 \quad \ldots (3)$$

where W_{max} is the nominal fluid weight of the full bag (100 g for a 100 mL saline bag, since the density of normal saline is approximately 1.0046 g/mL). The value of L is constrained to [0, 100] using a saturation function to prevent out-of-range display values during sensor startup transients. This formulation ensures that the weight of the empty bottle (approximately 32 g in the experimental setup) does not contribute to the displayed percentage, unlike two-point calibration approaches reported in [9] and [14].

D. Alert and Notification Subsystem

MediDrip implements a three-tier alert system governed by configurable percentage thresholds. Table I summarises the alert tier definitions and corresponding actuator states. The green LED (GPIO25) indicates normal saline levels above 60%. The yellow LED (GPIO26) activates when level falls between 25%-60%, providing early warning to nursing staff. Below 25%, the red LED (GPIO27) activates and the buzzer (GPIO5) is driven HIGH, producing a continuous 2.7 kHz tone. Simultaneously, Blynk virtual pin V2 is set to 1, illuminating the alert LED widget on the remote dashboard and triggering a Blynk automation notification.

E. Cloud Communication

The ESP32 connects to the hospital Wi-Fi network using the Arduino WiFi.h library. Blynk.begin() establishes a persistent TCP connection to the Blynk cloud server (blr1.blynk.cloud). A BlynkTimer object calls the data transmission function every 2000 ms using a non-blocking interrupt-driven approach, preventing delay() calls that would disrupt Blynk.run() and cause connection drops. Weight (V0), percentage (V1), and alert status (V2) are written to Blynk virtual pins using

Blynk.virtualWrite(), which the dashboard Gauge, Label, and LED widgets poll at 1 Hz. The Blynk platform provides automatic reconnection on transient Wi-Fi interruptions, ensuring continuity of monitoring.

TABLE I

Alert Tier Definitions and Actuator States

Tier	Level Range (%)	LED State	Buzzer	Blynk V2	Clinical Action
Normal	60% – 100%	Green ON	OFF	0	No action required
Low	42% – 60%	Yellow ON	OFF	0	Prepare replacement bag
Critical	0% – 25%	Red ON	ON	1	Immediate nurse alert

IV. EXPERIMENTAL SETUP AND IMPLEMENTATION

A. Hardware Components

The hardware platform was assembled on a breadboard prototype with the following principal components: (i) ESP32 DevKit V1 (Xtensa LX6 dual-core, 240 MHz, 520 KB SRAM, 802.11 b/g/n Wi-Fi); (ii) HX711 24-bit load cell amplifier module; (iii) 5 kg single-point bending beam load cell; (iv) 1.3-inch OLED display (SH1106 driver IC, 128x64 resolution, I2C interface); (v) tri-color 5 mm LEDs with 220-ohm current limiting resistors; (vi) 5V active buzzer; and (vii) USB 5V 2A power supply. The total bill-of-materials cost was estimated at USD 12.40 at retail component pricing, significantly below commercially available IV monitoring solutions.

B. Software Environment

Firmware was developed using the Arduino IDE 2.3.2 with the ESP32 Arduino Core 2.0.14. Key libraries included: HX711 by Bogdan Necula (v0.7.5), BlynkSimpleEsp32 (v1.3.2), Adafruit SH110X (v2.1.10), and Adafruit GFX (v1.11.9). The Blynk cloud template was configured with three Integer-type datastreams on virtual pins V0, V1, and V2. The web dashboard comprised a Gauge widget (V1, range 0-100%), a Value Display widget (V0, unit: grams), and an LED widget (V2). All firmware was version-controlled using Git.

C. Calibration Procedure

Calibration was performed according to the three-point protocol described in Section III-C. Raw ADC values were recorded over 60-second windows (60 samples at 1 Hz) for each calibration condition to obtain stable mean references. The calibration constants obtained were: R_noload = 263,155 ADC units, R_bottle = 240,622 ADC units (32 g empty HDPE bottle), and R_full = 174,000 ADC units (100 mL saline bag, total weight 130 g). These constants were hardcoded into firmware as preprocessor macros.

D. Evaluation Protocol

Experimental validation was conducted across 30 independent drip cycles using 100 mL 0.9% sodium chloride (normal saline) bags. For each cycle, the bag was filled to nominal volume, mounted on the load cell, and allowed to drain through a standard IV administration set at a flow rate of approximately 20 mL/hr (controlled by a roller clamp). Weight readings from MediDrip were compared against a reference laboratory balance (Kern PCB 350-3, resolution 0.001 g, accuracy ±0.002 g) measured simultaneously at five-minute intervals. Alert trigger latency was measured as the elapsed time between the measured weight crossing the 42% threshold and the receipt of the Blynk virtual pin V2 update at the dashboard client, using network-synchronized timestamps.

E. Evaluation Metrics

System performance was evaluated using the following metrics: (i) Mean Absolute Error (MAE) of weight measurement in grams; (ii) Mean Absolute Percentage Error (MAPE) of level percentage; (iii) alert trigger latency in seconds; and (iv) system uptime percentage over 72 continuous hours of operation. These metrics were selected to align with clinical requirements for IV monitoring accuracy as discussed in [3] and [18].

V. RESULTS AND DISCUSSION

A. Weight Measurement Accuracy

Across 30 drip cycles and 900 comparison data points, MediDrip achieved a Mean Absolute Error (MAE) of 1.8 g against the reference laboratory balance. The Mean Absolute Percentage Error (MAPE) for saline level percentage was 2.3%. The maximum observed single-point error was 4.1 g, occurring during the initial 30 seconds following bag placement before sensor readings stabilised. After a 45-second settling period, the maximum error was reduced to 2.9 g. These results represent a 40% improvement in weight accuracy over the two-point calibration approach reported by Rao and Venkat [14], which reported a MAE of 3.0 g under similar test conditions.

B. Alert Latency

The mean alert trigger latency from threshold breach to Blynk dashboard notification was 1.18 seconds (standard deviation: 0.23 s) across 30 threshold crossing events. The minimum observed latency was 0.81 s and the maximum was 1.72 s. All latency measurements were below the 2-second clinical threshold identified by Li et al. [18] as necessary for real-time monitoring systems. Local buzzer and LED alerts were observed to trigger within 40 ms of threshold crossing, determined by the 2-second BlynkTimer interval and the instantaneous GPIO response of the ESP32.

C. System Reliability

Over 72 continuous hours of operation (3 test units in parallel), the MediDrip system maintained 99.7% uptime. Two brief disconnections were recorded, both attributed to router-level Wi-Fi interruptions, with automatic Blynk reconnection restoring connectivity within 8 seconds in both cases. No firmware crashes or watchdog timer resets were observed. The HX711 readings remained stable with a coefficient of variation below 0.15% during periods of no weight change, confirming adequate electrical noise isolation.

D. Comparison with State-of-the-Art

Table II presents a comparative analysis of MediDrip against representative prior systems across key performance dimensions. MediDrip demonstrates competitive or superior performance in weight accuracy and alert latency while offering the lowest bill-of-materials cost among systems with cloud connectivity. The inclusion of local tri-color LED alerting, absent in most prior cloud-connected systems, provides a critical failsafe when Wi-Fi connectivity is unavailable.

TABLE II

Comparative Analysis of IV Drip Monitoring Systems

System	Sensing Method	Weight MAE (g)	Alert Latency (s)	Cloud?	Local Alert?
Rajesh et al. [5]	IR Drop Counter	N/A	2.8	No	Buzzer
Sharma et al. [9]	Load Cell (2-pt)	3.0	N/A	No	LED
Rao & Venkat [14]	Load Cell + Wi-Fi	3.0	3.1	Yes	No
Ghosh et al. [6]	Ultrasonic	~8.0	2.5	No	Buzzer
Patel et al. [7]	Camera + CNN	~5.0	4.2	Yes	No
MediDrip (Proposed)	Load Cell (3-pt)	1.81	1.18	Yes	NO

E. Limitations

Several limitations of the current prototype were identified. First, the system is calibrated for a specific 100 mL saline bag type; different bag sizes or materials require recalibration. Second, the load cell exhibits thermal drift of approximately 0.1 mV/degree Celsius, which may introduce errors of up to 2 g in environments with significant temperature variation (greater than 10 degrees Celsius change). Third, the Blynk free-tier plan imposes a messaging rate limit of 100 messages per second across all devices on the account, which must be considered in multi-bed deployments. Finally, the current mechanical mounting design does not accommodate bag sway during patient repositioning, which may cause transient measurement spikes.

VI. CONCLUSION

This paper presented MediDrip, a cost-effective IoT-based intravenous drip monitoring system that employs a load cell with a novel three-point calibration methodology to accurately measure remaining saline volume and percentage in real time. The system integrates an ESP32 microcontroller, HX711 24-bit ADC, OLED display, tri-color LED indicators, audible buzzer, and Blynk cloud connectivity to provide comprehensive local and remote alerting. The primary novel contribution, the three-point calibration that isolates fluid weight from bottle tare weight, yields a mean absolute error of 1.8 g and level accuracy of ±2.3%, representing a meaningful improvement over prior two-point calibration approaches. Alert latency of 1.18 seconds satisfies the sub-2-second clinical requirement for real-time IV monitoring systems.

The system was validated across 30 drip cycles and 72 hours of continuous operation, demonstrating 99.7% uptime and robust reconnection behaviour under transient Wi-Fi interruptions. At a bill-of-materials cost of approximately USD 12.40, MediDrip is positioned as a practical solution for resource-constrained healthcare environments in developing nations.

Future work will address several identified limitations. Temperature compensation using an onboard thermistor will be incorporated to mitigate thermal drift. An adaptive multi-bag calibration interface will be developed to support different bag sizes without firmware reflashing. The system will be extended to a multi-bed monitoring dashboard using Firebase Realtime Database with time-series analytics. Integration with hospital nurse call systems via MQTT protocol and a mobile push notification module via Blynk's automation engine are also planned. Long-term clinical trials in a hospital ward setting are needed to validate performance under real-world operational conditions.

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