Low-Power Analog Bayesian Classifier for Diabetes Detection

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Table of contents

1. Introduction

Analog Classifiers

- Hardware equivalent of software-based ML classifiers
- Built using Bump Circuits + **Bayesian/Gaussian models**
- Can directly classify analog input signals

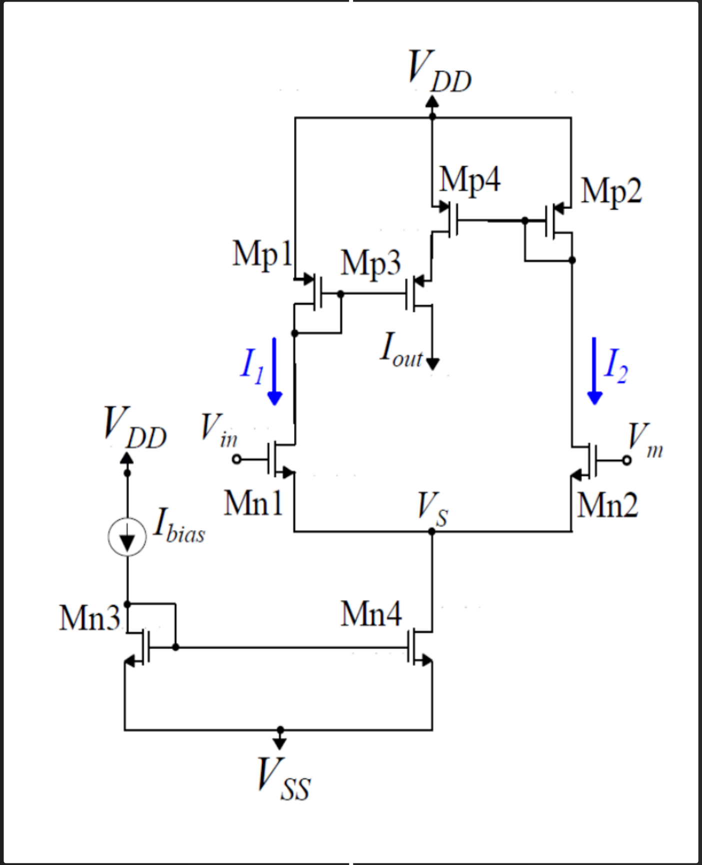
Why Analog?

- **Ultra-low power** – ideal for edge/wearable devices
- Real time processing of sensor outputs

Application: Diabetes Detection

- Diabetes = major global healthcare challenge
- Goal: enable **smart, low-power medical wearables.**
- Stepping stone for advanced health monitoring.

2. Initial Bump Design



2.1 – Delbruck’s Design

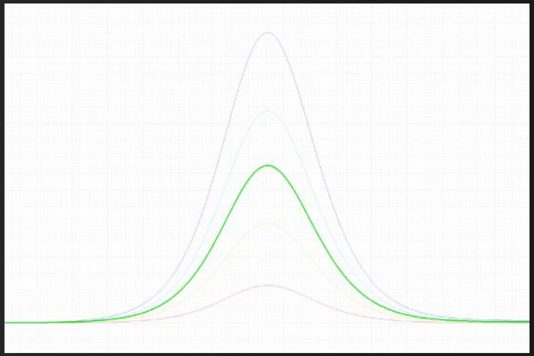
- Proposed by T. Delbruck in 1991
- Two main blocks: Differential Input and Assymetric Current Correlator
- Sub-threshold operation
- Generates Gaussian-like current output
- $Iout = \frac{I_{bias}S}{4\cosh^2(\frac{\kappa V_{in} - V_{mean}}{2})}$
- I_{bias} and V_{mean} control the height and the mean value, respectively.
- Quantity S is given as such:

$$S = \frac{\left(\frac{W}{L}\right)_{3,4}}{\left(\frac{W}{L}\right)_{1,2}}$$

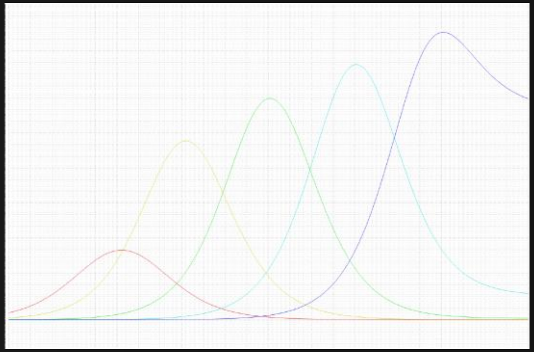
- κ is the slope factor and V_{in} is the input voltage
- Theoretical V_{mean} tunability

2.2 – Tunability of original bump

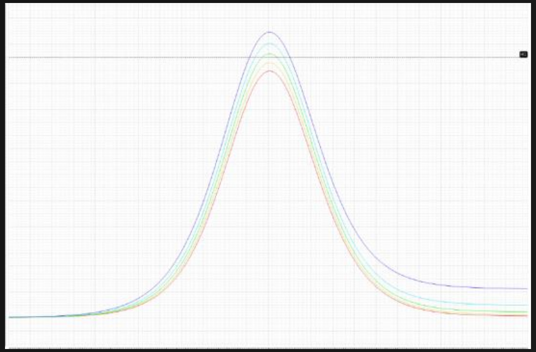
I_{bias} sweep



V_{mean} sweep



V_C sweep



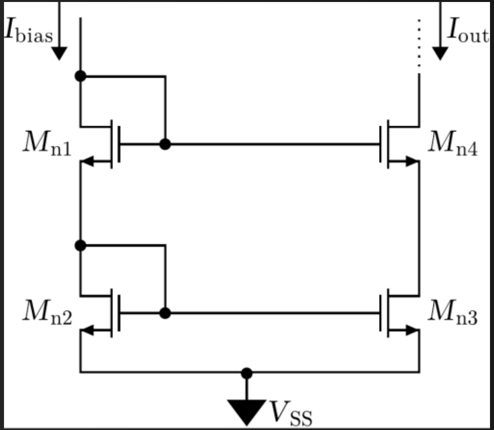
3. Updated Gaussian Bump Design

3.1 Current Mirror

- Biases the differential input
- Finite output resistance → source fluctuations leading to bad performance when shifting V_{mean} to lower values
- Mitigations
  - Increase channel length (L); $r_{ds} \cong\propto \frac{1}{\lambda * I_D} \propto \frac{L}{I_D}$
  - Change configuration

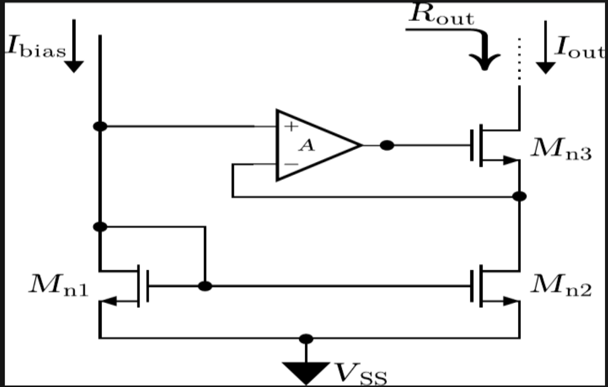
Cascoded Current Mirror

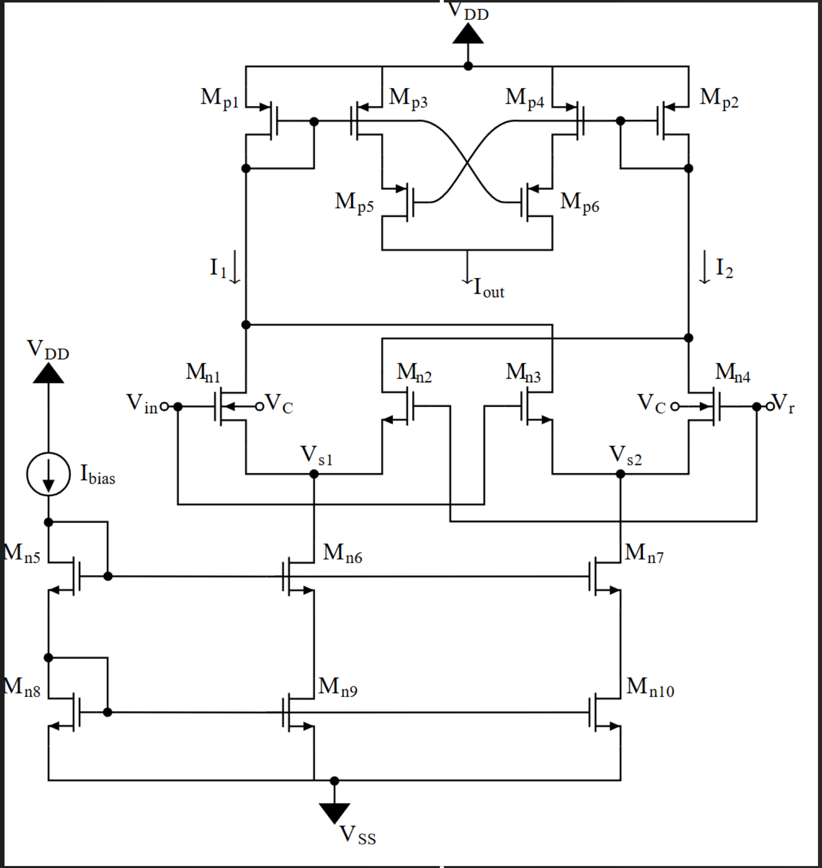
$$r_{out} \cong g_m * r_{ds}^2$$



Opamp Feedback Current Mirror

$$r_{out} \cong g_{m3} * r_{ds3} * r_{ds5} * (A + 1)$$





3.2 – Updated Design

Differential Difference Pair (DDP):

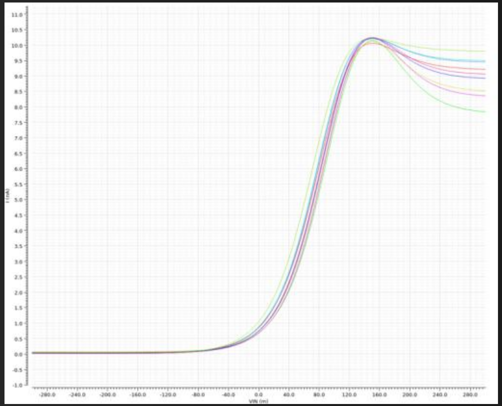
- Used as high-linearity **voltage-to-current** converter
- Provides tunability and better common-mode rejection than a simple differential pair
- M_{n1} and M_{n4} are bulk controlled
- Sizing Considerations:
  - W/L ≅ 1 with larger devices
  - $W_{2,3} = 3 * W_{1,4}$ in order to eliminate offset

Symmetric Current Correlator (SCC):

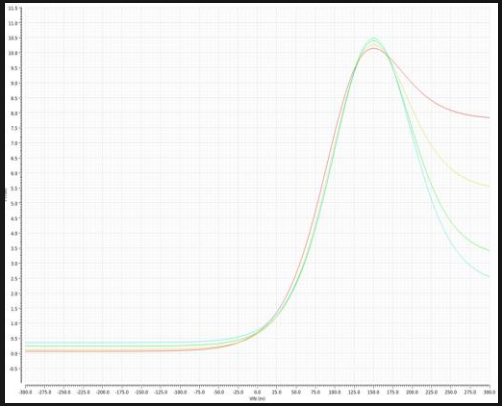
- Eliminate asymmetries caused by original design
- Sizing considerations:
  - Keep all transistors in the subthreshold region
  - Larger W offers more voltage headroom

3.3 – Fingers and Multipliers for the SCC

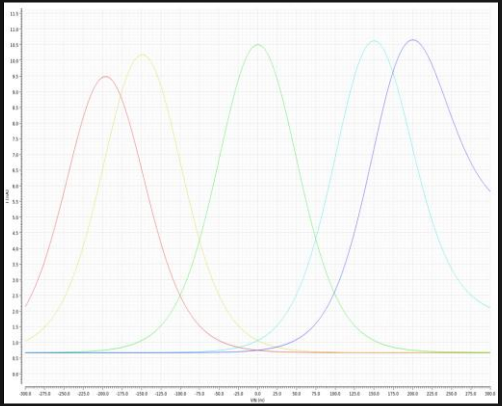
F = 1, m = 1, 2, 4, 6



F = 2, m = 1, 2, 4, 6

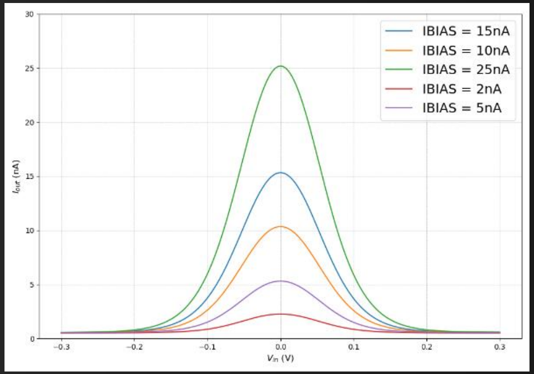


F = 8, m = 10

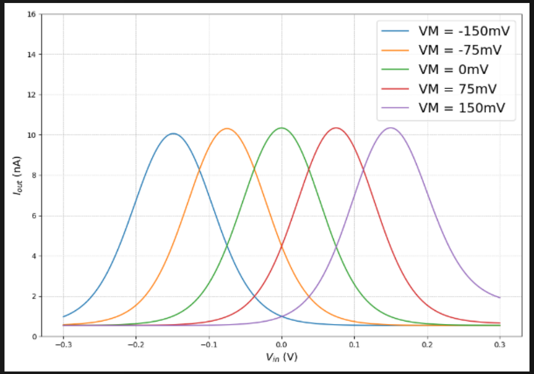


3.4 – Tunability of our design

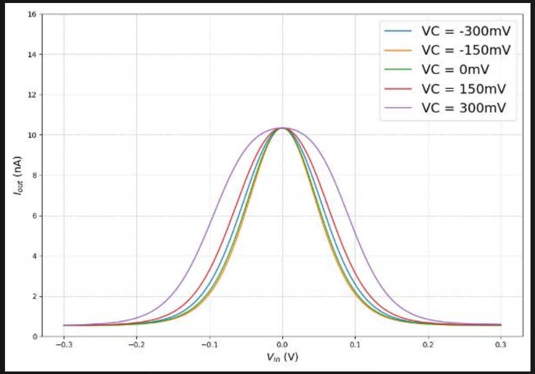
I_{bias} sweep



V_{mean} sweep



V_C sweep



4. Classifier Architecture

4.1 – Theoretical Models

Gaussian Mixture Model (GMM):

- Each class represented as a mixture of Gaussian functions
- Probability density for input *x*:

$$p(x|C_k) = \sum_{i=1}^{n} w_{k,i} \cdot \mathcal{N}\left(x; \mu_{k,i}, \sigma_{k,i}^2\right)$$

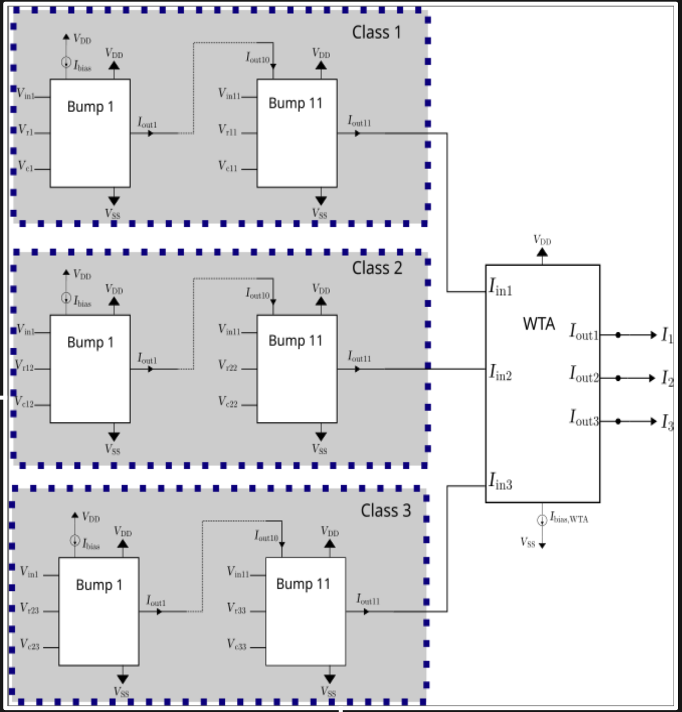
Bayesian Classification:

- Posterior probability

$$P(C_k|x) = \frac{p(x|C_k) \cdot P(C_k)}{\sum_j p\left(x|C_j\right) \cdot P\left(C_j\right)}$$

- Decision rule: assign *x* to class with **highest posterior probability**

4.2 – Hardware Implementation



- Implements Bayesian model: maps input features to class probabilities
- Each class: n cascaded Bump circuits (n = number of input features; 11 for diabetes dataset)
  - *Cascaded:* output of one bump serves as input to the next, multiplying the feature likelihoods to compute the joint probability.
  - Each feature is converted into V_{mean} and V_C values based on the dataset and code preprocessing
- Each class outputs I_{out}, with peak magnitude indicating the likelihood of belonging to that class
- Winner-Take-All (WTA) circuit performs the ***argmax*** operator

$$\hat{C} = \arg\max_k I_{out,k}$$

- Digital output suitable for further processing

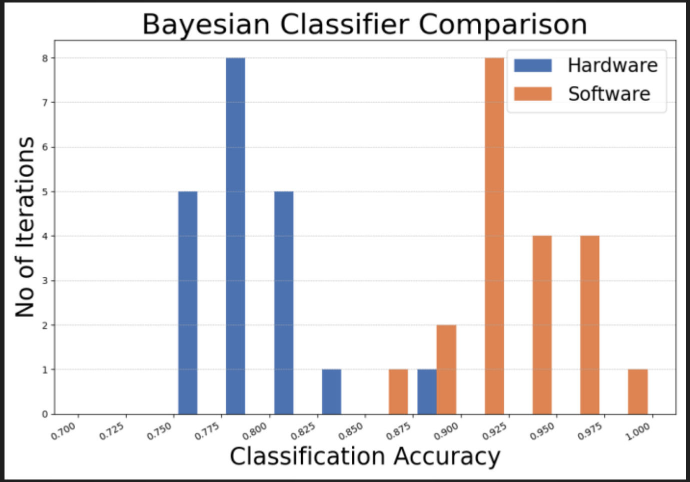
5. Inference

5.1 – The Diabetes Dataset

- **Samples:** Real-world patient data with multiple risk factors
- Features (11 total):
    - Demographics: Gender, Age, BMI
    - Kidney function: Urea, Creatinine
    - Glucose control: HbA1c
    - Lipid profile: Chol, TG, HDL, LDL, VLDL
- **Target Classes (multi-class):**
    - 0 = Non-Diabetic
    - 1 = Diabetic
    - 2 = Predict-Diabetic (at risk)
- Features vary in scale and range → require normalization & mapping to circuit parameters (V_{mean} and V_C)
- Chosen for relevance: Diabetes = a critical health issue with global prevalence

5.2 – Performance Summary

Software vs Hardware



Performance Summary

Method	Best	Worst	Mean	Std.
Software	0.99	0.87	0.93	0.03
Hardware	0.89	0.75	0.79	0.03

Technology	Power Supply	Power Consumption	Classification Speed
130nm	0.6V	114nW	20K

6. Overview & Conclusions

Results

- Tested on a real diabetes dataset
- Achieved ≅80% accuracy (vs. ≅93% in software)
- Ultra-low power: 114nW at 0.6 V supply

Key Takeaway

- Proof-of-concept for low-power, real-time medical classifiers
- Potential path toward smart wearable devices for health monitoring

Future work

- Improve accuracy with extended feature handling
- Integration with on-chip sensors & larger datasets

Thank you!

Do you have any questions?

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