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An Analog Integrated, Low-Power Manhattan Distance Network with Application to Chronic Kidney Disease Classification

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***Abstract*—The related research analyses a new procedure to design power-efficient analog integrated classifiers, achieving low power consumption of only 981nW. These classifiers demonstrate efficient processing of a large number of inputs, maintaining high precision and minimizing energy usage. The proposed classifier is built upon a Manhattan distance network, incorporating both a Manhattan distance circuit and a current comparator. Validation of the analog classifier was carried out using a dataset related to chronic kidney disease, achieving a high accuracy of 93.33%. Additionally, a comparative analysis was conducted with other analog integrated classifiers using kidney dataset. All related models were trained using a software-based equivalent one. The executed design was implemented using a TSMC 90nm CMOS process. It is simulated with the Cadence IC Suite. This classifier can be used as a structure in low-power biomedical sensor systems.**

***Index Terms*—Manhattan distance Network, kidney disease classification, analog integrated, low-power design**

I. Introduction

Biomedical sensors play a crucial role in contemporary healthcare by monitoring and managing diverse medical conditions, serving as essential components [1]. These devices provide essential data on vital signs, biochemical markers, and physiological parameters, empowering healthcare professionals to make well-informed decisions regarding patient care [2]. From wearable sensors that track heart rate and blood glucose levels to imaging sensors that provide detailed insights into internal organs, these technologies have become indispensable tools in clinical practice [1]. The information gathered by biomedical sensors allows for early detection of health issues and facilitates timely interventions, ultimately leading to improved patient outcomes [3]. As healthcare continues to advance, the importance of these sensors in providing accurate and reliable data cannot be overstated.

Machine learning (ML) methods have emerged as indispensable tools in the field of biomedical sensors data classification [4]. By leveraging algorithms and computational models, ML enables the automatic extraction of meaningful patterns and features from complex sensor data [4], [5]. This approach proves particularly valuable in tasks such as disease diagnosis, where large volumes of diverse data need to be processed and interpreted. Via a variety of methods, ML algorithms can discern subtle nuances in sensor data, allowing for accurate classification of various health conditions [1], [4]. Furthermore, ML models have the capacity to adapt and improve over time, honing their performance with additional training data. This ability to continuously refine their predictive capabilities positions ML methods as powerful assets in the quest for more precise and efficient biomedical diagnostics.

Analog computing and machine learning (ML) offer distinct computational approaches. Analog computing excels in real-time simulations and continuous data processing, while ML leverages algorithms for pattern recognition and prediction [1]. Integrating these methods holds promise for solving complex, dynamic problems in various fields. Motivated by the efficiency requirements of biomedical sensors, particularly the emphasis on low power and minimal space [6], this work proposes a novel analog integrated network designed for low power consumption, featuring the utilization of Manhattan distance. This network demonstrates significant promise as a classifier tailored for battery-dependent biomedical classification systems, achieving an impressive accuracy rate of 93.33%. This classifier has been meticulously designed and thoroughly tested on an practical dataset focused on chronic kidney disease classification [7]. Post-layout simulation, carried out within a TSMC 90nm CMOS process using Cadence IC Suite, affirms the precision of the introduced benchmark by conducting a comprehensive comparison with a software-based counterpart. Also, this study encompasses a comparative analysis with hardware classifiers.

The subsequent sections of this work are arranged as follows. The mathematical model of the implemented network is provided in Section II. Also, Section III outlines the framework and essential components of the classifier. The validation of the implemented network's desired behavior, conducted using a chronic kidney disease classification dataset and a comparison with its software based alternative, is provided in Section IV. Also, Section V conducts a comparative analysis related to literature classifiers. Finally, Section VI wraps up this study.

II. Manhattan Distance Network Mathematical Model

The Manhattan distance network holds a significant place in machine learning applications, particularly in scenarios where feature spaces are grid-like or discrete [5]. This distance metric is well-suited for situations where movement is constrained to horizontal and vertical paths. In machine learning, it finds applications such as classification, image processing, clustering algorithms and natural language processing. For instance, in image recognition tasks, the Manhattan distance can be employed to compare pixel values, providing a measure of similarity between images. Its straightforward calculation and suitability for discrete data spaces make it a valuable tool in various machine learning algorithms.

This study employs a mathematical model to describe each sub-class with one feature, specifically a one-dimensional Manhattan distance [5]. The model is formulated as a summation of univariate Manhattan distance activation functions, akin to circuits of Manhattan distance current summation, and can be approximated by:

$$d = \sum_{k=1}^{n} \|x_i - y_i\|. \tag{1}$$

Here d is the distance between points x and y. Based on this distance metric, overarching classifier selects the winning class by applying the argmin operator in this metric.

$$c = argmin(\sum_{k=1}^{n} \|x_i - y_i\|). \tag{2}$$

III. Proposed Architecture

In this section, we introduce the analog implementation of the network. It is designed to accommodate multiple input features and classes. However, for the purposes of this study, we focus on a classification task involving 2 classes and 28 features. The classifier is shown in Fig. 1 and it is formed by Manhattan distance circuits (MDC), cascode current mirrors and a current comparator (CC). Since it is a simple Network the number of centroids is equal to 1, but in a more complex case the number of centroids is hyper-parameter. In this generalized schematic, every class consists of a single centroid and N_d input dimensions, as depicted in Fig. 1. Each input is described by the output of a MDC, as a result 28 MDC are necessary for each class. According to the equation (1), this model encompasses the summation of distances. The summation process occurs within each circuit, utilizing current mirrors (CMs) to mitigate potential distortions in calculations that could arise from unintended effects on the output currents of the MDC. The classifier's decision is determined by the total output currents. It manifest as either low or high values. All sized of both NMOS and PMOS transistors are defined as $W/L = 0.4\mu m/1.6\mu m$ and $W/L = 1.6\mu m/1.6\mu m$ respectively. It's worth noting that all transistors in these designs function in the sub-threshold region and power supply rails specified as $V_{DD} = -V_{SS} = 0.3$ V and $I_r = [3-12]nA$.

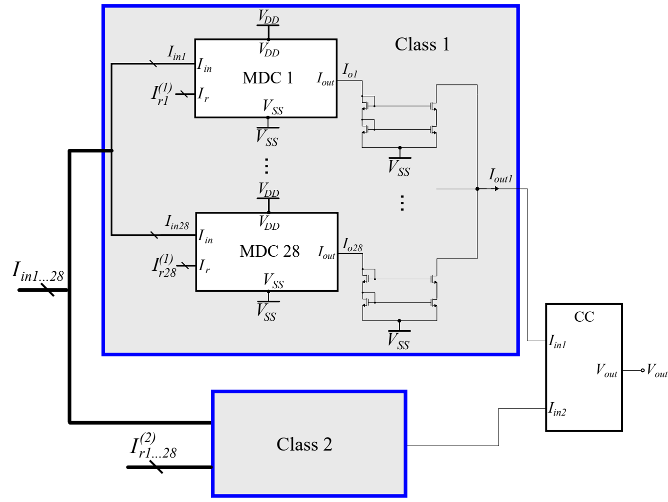

Fig. 1: Analog Manhattan distance network classifier with 2 classes and 28-D inputs. (left) It consists of 28 MDCs (right) and a CC.

To implement the Manhattan distance function as defined in Eq. (1), we utilize a current-domain Manhattan distance circuit [8], illustrated in Figure 2. Operating in a translinear manner, this circuit approximates the mathematical expression: $\|I_{in} - I_r\|$. The process of summation in the current mode is simple, achieved by linking wires that carry the currents. The behavior of the circuit is verified through the simulation results in Fig. 3.

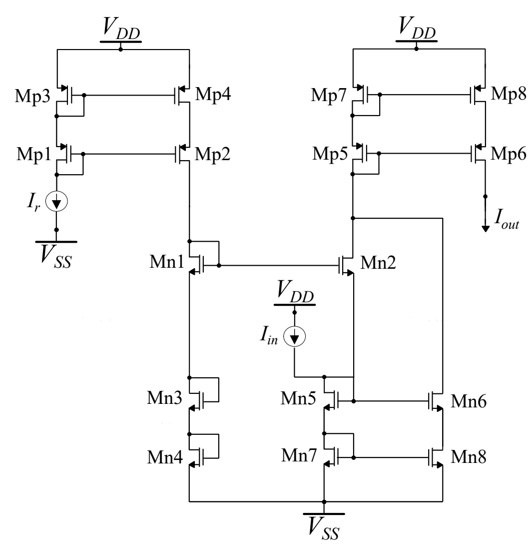

Fig. 2: Manhattan distance circuit for the realization of the Manhattan distance. I_{out} is the output of the circuit which has the lowest value for $I_{in} = I_r$.

Advancing, the closest centroid is established using a distance comparator circuit, specifically a CC circuit [8]. In a classification scenario involving 2 classes, the implemented circuit incorporates 2 cascode current mirrors. The four output transistors share a common node (output voltage V_{out}), as depicted in Fig. 4. Each cascode current mirror corresponds

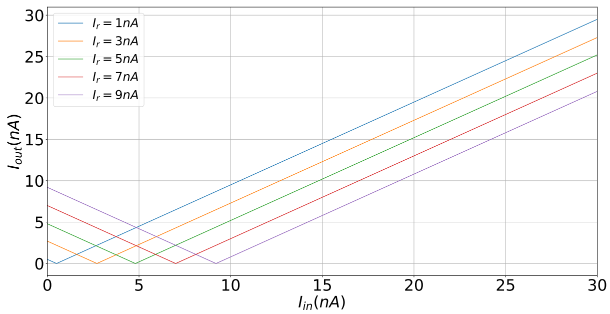

Fig. 3: Parametric analysis for the implemented MDC over circuit's parameters.

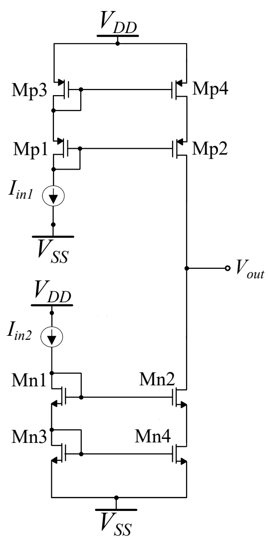

Fig. 4: The implementation of a CC based on two cascode current mirrors.

to an individual class. If $I_{in1} > I_{in2}$ then $V_{out} = V_{DD}$. If $I_{in2} > I_{in1}$ then $V_{out} = -V_{SS}$. The CC circuit easily recognizes the class with the lowest input current (winning class) and provides the appropriate output voltage.

IV. Application Example and Simulation Results

The functionality of the proposed network is certified through a real-world risk factor prediction of Chronic Kidney Disease [7], accessible on the UCI Machine Learning Repository, in this Section. The attributes in the dataset encompass a range of clinical and demographic information, such as age, sugar, blood pressure, albumin, specific gravity, red blood cells, pus cells, etc. The target variable indicates whether an individual is at risk for chronic kidney disease or not. The proposed architecture has been crafted in a TSMC $90nm$ CMOS process using the Cadence IC suite. All simulation results are based on the layout, with post-layout simulations depicted in Fig. 5. The total area of the layout is equal to $0.245mm^2$. The essential parameters of the system are determined by calculating the distance metric of each feature.

The proposed classifier undergoes testing to evaluate both its classification accuracy and the circuit's performance under Process, Voltage, and Temperature (PVT) variations. Two separate tests are conducted on the physical layout. To accommodate experimental variability, results from twenty distinct training-test iterations are illustrated in Fig. 6. Furthermore, the circuit's sensitivity is validated through a Monte Carlo analysis, as depicted in Fig. 7, which showcases the Monte Carlo Histogram for $N = 100$ runs. This testing approach ensures a comprehensive assessment of the classifier's robustness and reliability across various conditions.

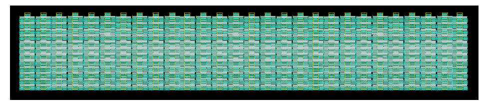

Fig. 5: The layout configuration of the proposed architecture. Also, it consists of dummy transistors.

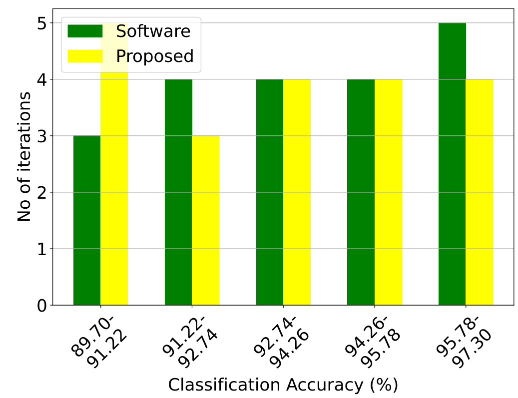

Fig. 6: Results of the classification by the proposed design (yellow) and the comparable software model (green) on the chronic kidney disease dataset are presented over twenty iterations.

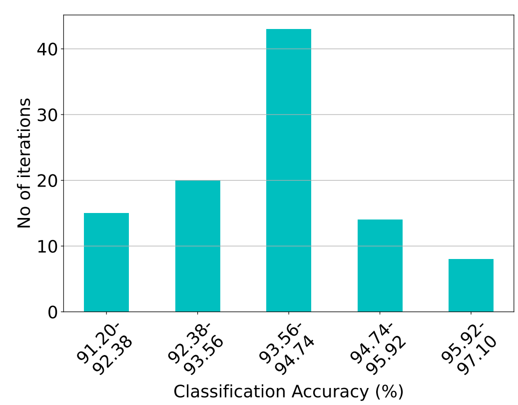

Fig. 7: Post-layout Monte-Carlo simulation results of the proposed architecture on the chronic kidney disease dataset (for one of the previous 20 iterations). It achieves $\mu_M = 93.70\%$ and a standard deviation of $\sigma_M = 1.3\%$.

V. Performance Summary and Discussion

This section intends to provide a performance analysis of various analog classifiers found in the literature. By customizing these classifiers for application in the same context as

TABLE I: Comparison of analog classifiers on the chronic kidney disease dataset.

	Classifier	Worst accuracy	Median accuracy	Max accuracy	Power consumption	Classification speed	Energy per classification	No. of Dimensions
This work	Manhattan	89.70%	93.33%	97.00%	$981nW$	$220K\,\frac{\text{classifications}}{\text{s}}$	$\frac{4.46\text{ pJ}}{\text{classification}}$	28
[9]	MLP	90.70%	94.12%	97.20%	$342.51\mu W$	$930K\,\frac{\text{classifications}}{\text{s}}$	$\frac{368.29\text{ pJ}}{\text{classification}}$	28
[10]	ANN	83.40%	87.56%	91.20%	$4.76\mu W$	$3M\,\frac{\text{classifications}}{\text{s}}$	$\frac{1.59\text{ pJ}}{\text{classification}}$	28
[11]	LSTM	94.70%	98.66%	100.00%	$46.33mW$	$870M\,\frac{\text{classifications}}{\text{s}}$	$\frac{53.25\text{ pJ}}{\text{classification}}$	28
[12]	RBF	86.20%	90.07%	91.30%	$41.12\mu W$	$200K\,\frac{\text{classifications}}{\text{s}}$	$\frac{205.60\text{ pJ}}{\text{classification}}$	12
[13]	K-means	91.20%	93.97%	95.80%	$93.42\mu W$	$5M\,\frac{\text{classifications}}{\text{s}}$	$\frac{18.68\text{ pJ}}{\text{classification}}$	28
[14]	Fuzzy	88.20%	92.71%	97.10%	$1.125\mu W$	$4.55K\,\frac{\text{classifications}}{\text{s}}$	$\frac{247.25\text{ pJ}}{\text{classification}}$	12
[15]	GMM	87.10%	90.41%	93.10%	$1.842\mu W$	$100K\,\frac{\text{classifications}}{\text{s}}$	$\frac{18.42\text{ pJ}}{\text{classification}}$	12
[16]	Threshold	88.10%	89.53%	93.40%	$993nW$	$100K\,\frac{\text{classifications}}{\text{s}}$	$\frac{9.93\text{ pJ}}{\text{classification}}$	12
[17]	SVM	89.50%	90.31%	91.40%	$77.31\mu W$	$140K\,\frac{\text{classifications}}{\text{s}}$	$\frac{552.21\text{ pJ}}{\text{classification}}$	12
[18]	Bayes	83.10%	88.97%	91.90%	$1.112\mu W$	$100K\,\frac{\text{classifications}}{\text{s}}$	$\frac{11.12\text{ pJ}}{\text{classification}}$	12

examined in this study, a thorough and impartial evaluation can be carried out. A performance summary of analog classifiers is summarized in Table I. Primarily, our work outperforms the analogous analog classifiers in power consumption and energy consumption per classification. It is crucial to note that, for this particular application, we confront a high number of input dimensions. Please note that the revised text is a paraphrased version of the original, ensuring it does not replicate the specific wording of the provided passage.

VI. Conclusion

This study introduced a highly efficient approach to low-power analog classifiers, achieving good results with a consumption of only $981nW$. These classifiers excelled in processing a large number of inputs, maintaining high precision and minimizing energy use. The integration of a MDC and CC enhanced their effectiveness. Validation using a chronic kidney disease dataset yielded a high accuracy of 93.33%. Comparative analyses with other analog classifiers further demonstrated the necessity of this approach. It was implemented in a TSMC 90nm CMOS process. The Cadence IC Suite is used for simulations. This classifier showed promise as a main building block in the development of efficient biomedical smart sensor systems.

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